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Opening and Closing Price Efficiency: Do Financial Markets need the Call Auction?

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Abstract

We model 73.62 million London Stock Exchange (LSE) trades and show that the LSE's high rate of failure to open at the opening auction only relates to low volume stocks. Low volume stock traders avoid trading until the open; this seems connected to their evading the informed trading-dominated opening auction. For the largest volume stocks, the opening auction provides highly efficient opening prices, while the lower volume stocks attain similar levels of price efficiency only after the start of normal trading hours (NTH). At the close however, all stocks only lose small fractions of informational efficiency achieved during the NTH.

JEL classification: G12; G14; G15

Keywords: Price efficiency; Price discovery; Trading activity; Call auction; London Stock Exchange

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1. Introduction

The question of how financial instruments' prices develop on financial platforms has fascinated both academic researchers and practitioners for decades. The introduction of computer-aided trading, and relatively more recently, algorithmic trading, has only increased this interest. The process of generating a fair price for an instrument can be quite complicated given possible information asymmetry. However, decades of relentless technological advancement has led to the development of ultra-quick information dissemination processes, which now feed directly into platform trades. The proliferation of information dissemination structures, such as bespoke real-time trading information providers and 24-hour financial markets news channels such as CNBC and Bloomberg, has now led to an unprecedented timely release of information to the market place. These streams of data feed directly into algorithmic trading strategies, which have been shown to improve trading quality by narrowing spreads, reducing adverse selection and enhancing the informativeness of quotes (see Hendershott et al., 2011). Even with these advancements, establishing an opening reference price after a market closure can still be a challenging process. Market closure may be due to the close of regular trading, trading suspensions or temporary halts. For traders, establishing a fair price after such closures is critical to trading strategy. The importance of the pre-open to price discovery is demonstrated by Biais et al. (1999) and Cao et al. (2000) who show evidence of 'learning' through the posting of non-binding quotes on the Paris Bourse and NASDAQ respectively. It is also important to note that opening prices may influence trader disposition throughout the trading day, and closing prices may be the basis for settling derivative contracts.

Given the significance of the opening and closing prices to trading, we investigate whether the call auction, one of the most popular opening mechanisms in major markets, yields efficient opening prices. We employ data from the world's oldest and fourth largest exchange by trading volume, the London Stock Exchange (LSE). The LSE is an interesting market to study because it is a hybrid trading platform. On the platform there is direct competition for order flow between participants (mainly institutional investors) in the broker-dealer market and others who directly submit orders to the limit order book. This is an interesting mix that naturally should enhance market quality. However, results obtained suggest that the opening call auction is only informative for the highest volume stocks, while for the low volume stocks, price discovery only really starts after the market opens as there is a high rate of failure to open at the call for small volume stocks. Furthermore, the dealer-broker trades entered during the pre-open, prior to the call auction, reveal very little information. The price discovery during this period is not significantly different from zero. Given the noise levels in the dealer-broker trades, only the highest volume stocks that succeed at the call are able to post significantly high levels of informational price efficiency during the LSE pre-open. For all stocks however, there is a high level of price efficiency during the normal trading hours (NTH), which only declines slightly after the NTH. We also find that small volume stock traders are likely to avoid trading during the opening call auction, due to the high level of information asymmetry/informed trading occurring during this period. Thus, the decision to avoid the opening call may be due to the need to avoid trading in an environment dominated by informed traders.

One may argue that the significance of the opening price has been reduced by the rise of Electronic Communication Networks (ECNs) and Broker Crossing Networks (BCNs), which make after hours trading possible, albeit with higher levels of informed trading and lower trading volumes (see for example Barclay and Hendershott, 2003). The price discovery process during the after hours trading period is also fraught with inefficiencies relative to the normal trading hours (NTH) session. The prices are more volatile, the adverse selection costs are higher, and thus spreads are generally wider. Barclay and Hendershott (2003) therefore find that price efficiency after hours is less than during the NTH because very little new information is released while trading is also thin. This means that even if post-NTH trading does provide some foundation for opening prices, most market participants are unlikely to trade on that basis because of the noise levels during the price discovery process once the market has officially closed. This underscores the significance of the opening price and the process that generates it. Thus markets around the world have evolved their opening practices in order to facilitate the efficiency of the price discovery process. The most widely adopted pre-open mechanism by platforms is the one we study in this paper – the call auction.

A stream of literature has examined the impact of the introduction of opening and closing call auctions on market quality. However, to our knowledge there is no linkage between informational efficiency and other market quality characteristics evolving in the opening auction, to the NTH market efficiency within an intraday modelling framework. The general approach has been to test whether the introduction or evolution of a trading system/mechanism positively or negatively influences market characteristics. A number of these studies mainly adopt an event study framework employing daily data (opening and closing prices). Thus none of the contributions have actually examined these issues on an intraday basis using high frequency trading data. Further, most of the focus has been on the introduction of closing auctions rather than opening auctions. For example, Chelley-Steeley (2008) and Chelley-Steeley (2009) investigate the market quality impact of the introduction of the closing auction on the LSE. Both studies document market quality improvements based on daily level data. The studies, however, do not isolate the direct market quality impacts of auction trades during the opening or closing call auction periods on continuous trading during the NTH. Pagano and Schwartz (2003) and Comerton-Forde et al. (2007) examine the introduction of the closing auction on the Paris Bourse and the Singapore Stock Exchange respectively; both papers suggest that the introduction of the call closing auction improves market quality. Comerton-Forde et al. (2007) also consider the impact of the closing auction in tandem with the opening auction without decomposing the impacts since both were introduced during the same month, and their study also employs daily data in an event study context. Another study, which focuses on the Singapore Stock Exchange, by Chang et al. (2008) confirms the "*spillover* effect", which was first documented by Pagano and Schwartz (2003) based on their analysis of trading on the Paris Bourse.

Since previous literature streams support the notion that the introduction of call auction enhances market quality, the past decade has seen the introduction of call auctions for closing and, in many cases, also the opening of trading venues across the world. There is a strong theoretical argument for congregating all available market liquidity at a single point in order to determine the fair price of an instrument. Schwartz (2001) asserts that this enhances the accuracy of the price discovery process. The view that the efficiency of the price discovery process is inextricably linked with liquidity is widely supported in the literature and has been further established by Chordia et al. (2008), amongst others. According to Madhavan (1992), since all traders are given access to the same prices at the same time, call auctions reduce information asymmetry. However, this comes at the price of higher information (and thus transaction) costs over time, as auctions can only be periodic at best. Barclay et al. (2008) also show that the consolidation of orders, which occurs during a call auction, rather than the nearness of traders or the involvement of market makers, is the vital factor for price efficiency in a market opening. Furthermore, their results imply that call auctions are more likely to absorb extreme liquidity shock without yielding inefficient prices and volatility. Amihud et al. (1990) find on the Milan Stock Exchange that when a continuous trading period is preceded by a call auction, volatility associated with that continuous trading session is lower than if it had not been preceded by a call auction. The improvement in market quality, usually associated with reduced volatility, perhaps explains why Schnitzlein's (1996) experimental study finds that under a call auction, despite no significant reduction in average price efficiency, there is a reduction in adverse selection costs incurred by uninformed traders. Interestingly, however, empirical evidence presented by Ellul et al. (2005) suggests that call markets are less suited than the broker-dealer system to deal with adverse selection. They also find that on days when uncertainty is higher, there is increased migration from the call market to the broker-dealer during the LSE pre-open, suggesting that traders prefer the broker-dealer when information asymmetry is on the rise. They argue that small stocks/orders traders are more likely to trade using the broker-dealer market rather than the call, because they are more likely to find counterparties by using that option (coordination theory). Somewhat contradictorily, their results also indicate that small orders obtain lower transaction costs on the call market when compared to the broker-dealer. Thus one would expect small stocks/orders traders to prefer the call market at the open and close, and that this should drive the availability of counterparties in the auction system for small stocks. Despite a number of contributions addressing issues around the use of the call auction to open or close, only a few published papers have examined inter-temporal links between the opening auction and continuous trading sessions. Brooks and Moulton (2004) provide evidence on interactions between the opening auction on an exchange, the NYSE, and the continuous regular trading day, but only focus on trading activities such as volume. Volume in itself does not imply liquidity or market efficiency; Johnson (2008) shows that volume and liquidity are unrelated over time and Chordia et al. (2008) show that liquidity is linked to market efficiency.

Our study is related to those of both Ellul et al. (2005) and Barclay et al. (2008). However, this paper is different from those two papers, since they focus on the contemporaneous comparison of two different trading mechanisms/options, whilst we focus on how the price discovery and other relevant trading parameters from one mechanism evolve as the market shifts to a different trading mechanism. Specifically, Ellul et al. (2005)

and Barclay et al. (2008) focus on traders' selection of trading mechanism(s) and the market's capacity to absorb order imbalances respectively.[1] We are also motivated differently; our aim is to examine first the efficiency levels of the opening price, and then how that evolves as the continuous trading period commences; we also observe the price efficiency during and after the closing call auction. This examination should shed some light on whether the opening auction period contributes to the NTH in terms of efficient price discovery. This main focus is also partially influenced by the findings of Barclay and Hendershott (2008). In their paper, which compares trading and non-trading mechanisms of price discovery, they suggest that the pre-open trading on NASDAQ contributes to the efficiency of the opening price. We aim to find out whether this holds when the pre-open is structured such that the opening price is determined by a call auction, and the NTH is a continuous order-driven market. If informed traders do not employ the opening call auction, given high failure rates to open, as implied by Ellul et al. (2005)[2], then the pre-open/opening auction price on the LSE may not provide a more informative or efficient opening price than say the first 10-20 minutes of the NTH. If, indeed, the opening auction/pre-open contributes to market quality during the NTH, then we expect the price efficiency for this period to be higher than, or equal to, other 10-minute periods across the NTH.

2. Institutional Background

2.1. Trading on the London Stock Exchange

Until 20th October 1997 when the LSE introduced an electronic order-matching system called the Stock Exchange Electronic Trading System (SETS) for all FTSE 100 stocks, it had

[1] Our research questions may also be linked to Amihud et al. (1990). However, the Milan Stock Exchange call method on which their study is based is significantly different from the one we study. Further, there are significant differences in the methodological approach they employ and ours; this is further amplified by the thin trading observed on the Milan stock exchange at the time of their study.

[2] Friederich and Payne (2007:1176) even went as far as stating that: *"The opening batch auctions in particular were never successful in London…"*.

functioned as a pure dealer market.[3] The FTSE 100 includes the largest firms by market value as listed on the LSE, and they account for about 81% of the total market capitalisation on the exchange. The introduction of SETS on the LSE encapsulates a shift from a strictly quote driven market to an order driven one. The SETS has since grown to become one of the most liquid electronic order books in the world. The LSE now operates as a hybrid market, with the dealer market and the SETS limit order book. Daily, continuous trading on the floor of the exchange is preceded by a 10-minute call auction at 07:50:00hrs London local time. However, generally during the pre-open (including prior to the opening auction), broker-dealer trades can also be reported. During the pre-open, limit and market orders may be entered and deleted at will, and all order book data are communicated to the market. In advance of the batch auction at 08:00:00hrs, the order book is suspended. An uncrossing algorithm subsequently runs to facilitate the execution of orders at prices that maximise the volume of instruments traded. Once buy and sell orders are crossed, indicative uncrossing prices for each instrument are displayed as the opening prices for the NTH.[4] The continuous trading period (NTH) is normally the longest period of the day and it concludes at 16:30:00 hrs. Thereafter, the closing call auction commences for five minutes starting at 16:30:01hrs. During the closing auction, limit and market orders can be submitted. If buy and sell orders are crossed during this period, the uncrossing price is released to the market as the closing price, as well as the indicative price at which crossed orders are executed. If there are remaining unexecuted orders following the uncrossing, an MOE is activated. And if the uncrossing price is at least 5% away from the VWAP (if there is no VWAP, then the last

[3] Subsequently, in September 1999, the most liquid FTSE 250 stocks were also migrated to SETS.

[4] Extensions to the opening auction can be activated under two scenarios. First, a Market Order Extension (MOE) could be activated for two minutes plus random 30-second end periods where there are unexecuted market orders on the order book after the uncrossing. Secondly, a Price Monitoring Extension (PME) can be activated where the indicative uncrossing price is at least 20% at variance with the final continuous session trade of the previous day. The MOE and PME can each only occur once for a trading session, thus all unexecuted orders after this point are retained on the order book for possible execution during the continuous trading phase. If the order book is not crossed for any instrument, the first automatic trade during the continuous trading session will be its opening price for trading on that day.

automatic trade), a PME is activated. Should the uncrossing price remain at least 5% away from the VWAP (or the last automatic trade) an Additional PME (APME) will be activated. The APME runs for 10 minutes plus a random 30-second end period. All these extensions can occur only once per closing of a trading day. If the closing procedure does not yield an indicative uncrossing price, then the last automatic trade during the trading day will be the closing price.[5]

3. Data

3.1. Sample Selection

We obtain ultra-high frequency data for SETS segments SETS0 and SETS1, which contain the most liquid FTSE 100 and FTSE 250 firms, from the Thomson Reuters Tick History (TRTH) database. The dataset covers 253 LSE trading days between 1st October 2012 and 30th September 2013, and contains approximately 1.65 billion observations (including quotes and transactions data); all observations are time stamped to the nearest millisecond. The following variables are included in the datasets: Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume.

In the dataset, quotes account for a little over 1.498 billion (90.79%) of the observations. This means that quotes are updated regularly relative to trading or order submission frequency, and thus we can easily obtain the best prevailing bid and ask quotes for each trade. We first employ the quotes in determining the prevailing best bid and ask quotes, as well as quote midpoints for each transaction; thereafter the quote rows are eliminated from the dataset, thus leaving us with only the trades, totalling 150,660,824. We identify a number of anomalies in the 150,660,824 trade observations that could only have

[5] See London Stock Exchange (2000a, 2000b, 2001 and 2013) for more details of the institutional framework.

been as a result of data input errors. In order to remove these input errors and to eliminate extreme price values, we delete all observations satisfying any of the following criteria:

1. Transaction price during the NTH is greater than the prevailing best ask price;
2. The quoted bid price exceeds the quoted ask price;
3. Quoted bid-ask spread, defined as the difference between the ask and the bid price, exceeds £4;
4. Quoted bid-ask spread divided by the transaction price is greater than 0.35;[6]
5. Any of the following variables is missing for that observation: price, volume, quoted bid and ask prices;
6. Non-FTSE 100 stock transaction;
7. Transaction is for FTSE 100 stock added to or removed from the index between the period 30th September 2012 and 30th September 2013.

We also eliminate all trades reported after 16:50:00hrs from the final sample because they are reported after the time a possible APME could have run each day. These conditions yield a final combined dataset with 73,616,187 transactions for 70 FTSE 100 stocks trading over the sample period. The 70 stocks account for 91.23% of the total FTSE 100 market capitalisation on 30th September 2013, the last date in our sample. To the best of our knowledge, the number of transactions used in this paper is larger than those used in any prior study of the microstructure of the LSE.

3.2. Sample Description

[6] Conditions 3 and 4 are inspired by Chordia et al. (2001); given the improved levels of trading frequency, the conditions stipulated in the earlier paper are adjusted for higher trading frequency.

The combined FTSE 100 stocks in the sample average a total trading value of over £21.54 billion per day from a daily average of 290,973 transactions. The total traded value over the 253 trading day-period is about £5.45 ($8.96) trillion. Table 1 shows the daily trading activity statistics for the sample used in this paper. Panels A and B present summaries for the exchange floor and the dealer market respectively, while Panel C shows daily averages of the transactions for both venues. In all panels, we rank the sample stocks into quintiles on the basis of transaction volumes for the sample period. Quintile 5 contains the 14 highest trading stocks by daily pound value, and Quintile 1 contains the 14 lowest trading stocks by daily pound value.[7] The panels are divided into three main time periods for each quintile: Pre-open (07:10:00hrs - call end), NTH (08:00:30hrs - 16:30:00hrs) and Post-NTH (16:30:01hrs - 16:50:00hrs). Pre-open is also further divided into Pre-opening call auction (07:10:00hrs - 07:50:00hrs) and the Opening auction (07:50:01hrs - call end). Post-NTH includes the Closing auction (16:30:01hrs - 16:38:00hrs) and the Post-close (16:38:01hrs -16:50:00hrs).

The highest grossing stocks have the highest number of transactions and pound value per day. The combined daily number of transactions (pound value) for the highest trading stocks is about six (207.33) times greater than the total for the lowest trading stocks; most of these are executed directly on the exchange floor. Also, most of the daily transactions occur during the NTH; almost 98% (284,548) of all transactions are recorded for the NTH. However, the trend is very different when one considers the value of those transactions; on an average day, the NTH accounts for only about 13.89% (£2.99 billion) of total traded value, while the post-NTH accounts for 84.86% (£18.28 billion). This is quite an interesting yet consistent occurrence for nearly every day in the sample. A closer look shows that the unusual phenomenon occurs only for the highest trading stocks grouped into Quintile 5; for

[7] The use of the transaction pound volume as a basis for segmenting stocks is driven by it being the most economically significant measure of trading activity, given that some orders may not result in a transaction but could be employed for quote stuffing or spoofing. Further the currency volume is a generally accepted basis for grouping stocks in price discovery-related studies in market microstructure (see as examples, Barclay and Hendershott, 2003; Bessembinder and Venkataraman, 2004).

the other four quintiles, the NTH easily accounts for 73.81% (£1.27 billion) of daily average traded value, while post-NTH only accounts for 23.04% (£395.48 million) of the daily average of traded value. Further, we find that the trades responsible for the massive values traded during the post-NTH period usually occur post-close and are off-floor dealer trades reported on the LSE. Since the large Quintile 5 post-NTH trades are off-floor broker-dealer trades, they are upstairs VWAP – volume weighted average price trades registered on SETS after the close (during and after closing auction). Institutional Investors are allowed to submit VWAP orders to the LSE dealer market, which can be executed at the close. VWAP orders do not include price, only the quantity to buy or sell, since the price is based on the weighted average price generated by the day's trading volume. They are usually very large trades, as demonstrated in the average size values presented in Panel C of Table 2. For example, the average post-closing auction size for the institutional dealer trades in the highest volume stocks is about 15 times as large as the corresponding trades on the exchange floor. The impact of these presumably pre-priced trades should be of interest; hence we extend the trading time of interest in our sample to 16:50:00hrs in order to capture their after hours effects. Their impact can, however, be isolated since our analytical approach is mainly based on estimating values within time-specific intervals.

INSERT TABLE 1 ABOUT HERE

While the post-NTH period is a relatively active interval of the day for all the quintiles, with even the first quintile averaging nearly 600 transactions per day in both venues, the pre-open is only significantly active for the highest volume quintile. However, pre-open trades are usually larger on average than trades during any other phase of the trading day, and this is confirmed in Panel C of Table 1. The average size for trades occurring in the pre-opening auction period is higher than other periods for four of the five quintiles, the only exception being the largest volume quintile where the post-NTH VWAP trades and the flurry of high volume closing auction orders tilt the balance. Given the propensity of large trades to elicit microstructure impacts, and because the period, with the exception of the largest volume stocks, is characterised by thin trading, we expect the two pre-open intervals to be noisier for lower volume stocks than the other periods of the day. Literature suggests that trading activity enhances price discovery, thus when trading is thin, the price discovery process is less efficient, although we also note that quotes are frequently posted and updated by market makers during the 10-minute auction period and prior to the auction period proper. Thus the level of market support available during the period prior to the NTH is not significantly less than during the NTH, and this may help to improve the price discovery process prior to the NTH. The question of whether posting of quotes can help improve price discovery is also dependent on the quote spreads. If the market makers are cautious, the posting and updating of quotes may not do much to help since the spreads will be wide in order to reflect adverse selection costs. We consider this issue in subsequent sections.

3.3. Trading Activity on the LSE

Figure 1 shows the daily volume per minute for the five quintiles; the logs of the values are plotted given the high variability in volume differences among the three trading periods. During the pre-open and prior to the call auction period, some trading is registered. However, as shown earlier in Table 1, these trades are few and are all executed in the dealer market, leading to a slow start to the pre-open. The average daily number of trades in the pre-opening call auction ranges from 7.37 to 23.45, from the lowest volume stocks to the highest. All stocks generally show high levels of variation in average trading values per minute prior to the opening call auction. For example, in the first minute of the pre-open included in the sample (07:16:00hrs), the average trading volume for all quintiles is about £33.65 million, this falls some 99.86% to approximately £48,714 at 07:50:00hrs, just milliseconds before the call auction period. The average daily trading volume then rises sharply to more than £173.33 million for the entire call auction from 07:50:00 - 08:00:00hrs. The final 50-odd seconds of the opening call auction itself accounts for approximately 58.41% of the call auction period trading value, as most of the orders are entered just before the auction algorithm runs. This volatile trend in early trading activity is well-documented in literature. For example, Barclay and Hendershott (2003) show a high level of correlation between trading volume and volatility during early NASDAQ trading. They show similar trading volume patterns to the ones we show in this paper. The highest trading volume is recorded for the first half-hour trading interval at the open, and volatility, measured as the standard deviation of half-hour stock return, also attains the highest level for the day during the same half-hour interval. The emerging U-shape pattern seen developing during the continuous trading period in Figure 1 is also well-documented in literature (see as an example, Chan et al., 1995). The volatility in trading volume around the open and close is also related to widening bid-ask spreads during that period as shown in both panels of Figure 4. This intraday behaviour is consistent with the pattern that has been extensively reported and discussed in the literature (see as an example, Brock and Kleidon, 1992).

The vast majority of trades during the opening call auction are for the highest volume stocks. Although, with the exception of the minute ending 16:35:00hrs when the closing auction algorithm usually runs, 08:00:00hrs has the highest trading value, the number of trades for the minute is very small in comparison to the rest of the trading day minutes. Microstructure literature suggests that large trades are more informative than smaller-sized ones, thus we expect that trades at 08:00hrs, and during other minutes of the entire pre-open, will be more informative than trades at any point during the NTH or post-NTH. We test this hypothesis in Section 4.2.2.[8]

INSERT FIGURE 1 ABOUT HERE

The average trading value following the opening call auction is sustained at over £170 million only on account of a steep increase in the value of lower volume stocks traded within the first 10 minutes of the NTH following their failure at the opening call auction. The lower volume stocks seem to have settled for a de-facto price referencing period between 08:00:00 - 08:10:00hrs because the trading value for Quintiles 4 to 1 then rise relative to the Quintile 5 levels during this period. To underscore this evolution, the trading value of the four lower quintiles combined approaches 45.14% of Quintile 5 trading value for the period. This is the highest level relative to Quintile 5 stocks, which the combined lower quintile stocks attain at any point during a typical trading day.[9] Afterwards, and for the rest of the day, the trading value settles down to a relatively stationary value, starting at approximately £2.87 million for the minute ending 08:11hrs, throughout the trading day, and prior to the closing call auction.

Although there are far fewer trades per minute in both the pre-open and post-NTH than there are in the NTH, their sizes are larger. In Figures 2 and 3, we show the mean and median trade sizes per minute for each quintile. Due to the large differences between the trade sizes in the three periods, we plot the logarithmic values of the mean and median rather than the raw values. With the exception of Quintile 5, the mean trade sizes are stationary once the market opens. The median values however are better behaved, with all the quintiles in

[8] The spikes seen in Figure 1 (as well as in Figure 2) are as a result of volumes of dealer (upstairs) trades from institutional traders. Their executions are as a result of tapping into unexpressed liquidity and thus do not result in any unusual price movements. These trades based on unexpressed liquidity seldom contribute significantly to price shifts since the upstairs market exists mainly to ensure that such does not occur (see Grossman, 1992; Seppi, 1990; Smith et al., 2001).

[9] Ellul et al. (2005) already report on the case of failure to open at the call. Their analysis shows that the call is not optimal for medium and small cap stocks. In this paper, we provide microstructure evidence that suggests this is a function of trading activity rather than market capitalisation. Further evidence provided in successive sections will explore this phenomenon further and provide more insight.

sync. This is because the median is less affected by extreme trade sizes executed off the floor through the broker-dealer channels. However, both measures tell the same story. 08:01:00hrs has the highest mean trade size for the entire NTH at £157,872.44, however this is only 0.85% (0.87%) of the average trade size at 07:16:00hrs (16:34:00hrs). These comparisons evidence the extent of variability in trade sizes during the different trading periods. With such large variations, we also expect dramatic variations in the identity of dominant market participants during the different trading periods. Specifically, we anticipate that more informed trades are being executed around the open and the close. We test this hypothesis in Section 4.3.

INSERT FIGURES 2, 3 AND 4 ABOUT HERE

4. Results and Discussion

4.1. Price Discovery on the London Stock Exchange

In the preceding section, we show the periodicity of trading activity, such that there is a high level of volatility around the open, and a generally high but stable level of trading activity for most of the trading day. We also observe how the average size of trades expand as the trading day draws to a close, and attains new levels during the period around the closing call auction. These competing effects, according to the literature (see for example Barclay et al., 1990; Chordia et al., 2011) determine the amount and timing of price discovery over daily trading cycles. Since our main interest in this paper is to examine the efficiency of the impounding of information in the prices of stocks around the open and close, i.e. the informational efficiency of price discovery, it is pertinent to commence our analysis by examining the intraday price discovery process across the entire trading day.

4.1.1. Weighted Price Contribution

We estimate the proportion of close-to-close price evolution discovered for different periods across the day, starting with the first period when off floor trades are sent to SETS between 07:10:00 and 07:20:00hrs. The periods for which we estimate the proportion of close-to-close price discovery include the first 10 and the final five 10-minute periods across the trading periods, as well as the block of trading hours between 09:00:00 - 16:00:00hrs. Since we measure period by period price discovery, we use the well-established weighted price contribution (WPC) (see Barclay and Hendershott, 2004; Barclay et al., 1990; Barclay and Warner, 1993; Cao et al., 2000; van Bommel, 2011).[10]

For each trading session/day and period k, we define the WPC as:

$$WPC_k = \sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right), \tag{1}$$

ret_s corresponds to the close-to-close return for stock s and $ret_{k,s}$ is the logarithmic return for period k and for stock s. In Equation (1), $\frac{ret_{k,s}}{ret_s}$ is a measure of relative proportion of the day's return given by stock s; $|ret_s| \big/ \sum_{s=1}^{S}|ret_s|$, which is the standardised absolute value of ret_s, which is the weighing factor for each stock. With the introduction of a weighing factor, smaller $|ret_s|$ are thus given small weights. The WPC is normally computed on a stock-by-stock basis and then averaged out across the stocks (see Cao et al., 2000). For this procedure, however, stock correlations, due to the common constituents, complicate statistical inferences about the mean. In our sample, we compute the WPC for each stock and obtain the average cross-sectionally across stocks and also compute WPCs for each day and the average across days; however, similarly to Barclay and Hendershott (2003), we only notice slight qualitative

[10] van Bommel (2011) show that the WPC is consistent; it is also the only unbiased and asymptotically normal measure for price discovery if the price process follows is a *driftless* martingale.

differences. Following Fama and MacBeth (1973), we obtain the mean WPC for each day, and employ the time series standard error of the daily WPCs for statistical inference.

INSERT TABLE 2 ABOUT HERE

Table 2 presents the WPCs for five quintiles and all the stocks combined; the results for each category of stocks are for 10-minute periods from 07:10:01 - 09:00:00hrs and 16:00:01-16:50:00hrs, as well as for the NTH period between 09:00:01 and 16:00:00hrs. There are four striking results emerging from this analysis. The first is the huge disparity in the proportion of price discovery recorded during the opening call auction period for Quintile 5[11] stocks on one hand, and the lower quintile stocks on the other. So striking is the difference that none of the lower quintile stock WPCs during the opening call auction are significantly different from zero. This clearly illustrates the general lack of informativeness of dealer transactions favoured by the lower quintile stocks during the call auction period. It further suggests that platform/floor orders/trades are still primarily the drivers of opening price change on the LSE; this much is underscored by the general lack of statistical significance for the pre-call period WPCs as well.[12] The results here are therefore consistent with the literature on the price impact of upstairs (dealer) trades (see Grossman, 1992; Smith et al., 2001). Second, approximately 30% or more of the close-to-close price discovery occurs during the call auction (08:00:00 - 08:10:00hrs) period for Quintile 5 (other quintiles) stocks. This shows that information accumulated overnight is incorporated into stock prices during the call auction for high volume stocks and within the first few minutes of the NTH for other stocks.

[11] There are a few Quintile 5 stocks (e.g. BAES, BLT and RIO) that suffer failure at the open call auction or post no trades/auction orders during the call auction; they are excluded from aggregate WPC of Quintile 5 stocks as well as further analyses of the 10-minute opening call auction period in order to ensure comparability of samples.

[12] The statistical significance and value of these estimates are at variance with those obtained by Ellul et al. (2005). While we do not postulate as to the reasons why, we expect that this difference is related to the fact that our sample is more recent by more than 13 years than Ellul et al.'s (2005) and the market has evolved over time. However, we note that our results are more in line with the observation of Friederich and Payne (2007) that the opening auction on the LSE hardly succeeds; their data is slightly more recent than Ellul et al.'s (2005).

It is tenable to expect that firm-relevant information is accumulated overnight since firms routinely time the releasing of their earnings and other reports for the post-NTH; these releases have also been shown to impact trading during after hours trading sessions (see for example Jiang et al., 2012). Further, price innovation in the early trading could have been influenced by broker-dealer activity. Thus for stocks that are not extensively traded/reported post-NTH, the first opportunity to incorporate new information will be during the first minutes of NTH or the pre-open. The puzzling aspect however is that the early broker-dealer trades do not reflect all of the overnight information, even if they are largely liquidity-driven as suggested by the upstairs trading literature (see Smith et al., 2001). Indeed price discovery does not really commence until the call auction period at 07:50:00hrs for all stocks; even then it only starts for the highest volume stocks and not the lower volume ones. For the lower volume stocks, price discovery only starts when the market opens at 08:00:01 hrs. This leads to the third striking aspect of the results. More than 50% of price discovery occurs before 09:00:01hrs in the morning for the lower quintile stocks. And if one considers the call auction period as well, then the same phenomenon is true for the highest volume quintile. Thus information is only normally incorporated into stock prices in small drips after the heavy absorption of information into stock prices in the morning. Finally, the fourth main observation from Table 2 involves the dramatic correction of prices recorded once the market closes. It does appear that the closing auction and the broker-dealer trades after the continuous trading session/NTH provide the opportunity for traders to revise downwards their valuation of stocks, especially for the higher volume quintile stocks.

The results obtained here are consistent with the conclusions from after hours trading analysis of NASDAQ stocks by Barclay and Hendershott (2003). Since the high volume stocks have a greater percentage, compared with other stocks, of their total daily trading in the pre-open (see Table 1), a large proportion of price discovery thus shifts to the pre-open, specifically to the opening call auction period. Thus, the question of why there is a high level of failure to open at the opening call for lower volume stocks is not only related to traders making a decision based on transaction costs; it may also be explained by the simple question of non-execution of trades. With lower trading volumes (including broker-dealer trades), such as a daily stock level average of 0.54 trades in the pre-open per day for Quintile 1 stocks, finding counterparty to trade with must be challenging; Ellul et al. (2005) make this argument by proposing the coordination theory as an explanation of low volume stocks traders' behaviour, by avoiding the call auction. However, it is perhaps possible to encourage low volume stock traders to use the opening call auction if a slight adjustment could be made to the call auction algorithm. At present, the algorithm is tailored to maximise volumes; it could perhaps prioritise price. For example, a volume weighted price during the call auction will ensure that low volume stock trades stand a better probability of execution. Low volume stock traders could then place market orders with a higher expectation of execution.

4.2. Price Discovery and Informational Efficiency

4.2.1. Unbiasedness Regressions

The WPCs indicate that approximately 30% or more of the close-to-close price discovery occurs during the call auction for Quintile 5 stocks and during the 08:00:00 - 08:10:00hrs period for other quintiles stocks. It is assumed that these respective periods set the pace for price discovery throughout the NTH and beyond, since they are the most informative intervals during the entire trading periods. Trades around the open and indeed the close are large. However, the spreads around those periods are large as well (see Figure 4). This implies price reversals around those periods as indicated by the negative WPC estimates around the close. The combination of potential price reversals and the sparse trading activity in the pre-open means that prices are likely to be noisy and thus inefficient. Considering the importance of the opening and closing prices to trading and investor confidence, we measure their informational efficiency by employing what Biais et al. (1999) call 'unbiasedness regressions'. The slopes of these regressions have a natural interpretation as the degree of noise during an estimated period. We examine efficiency of the price discovery process due to the significance of the opening price for investors. This is vital when one considers that a market's informational efficiency is a critical requirement for investor participation in markets. In order to compute the level of price efficiency for specified periods, for each stock and each day, Equation (2) is estimated separately for each time period; where ret_{cc} is the close-to-close return and ret_{ck} is the return from the close to the end time of period *k*:

$$ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_{ck} \tag{2}$$

According to Barclay and Hendershott (2003), the slope coefficient β measures the ratio of signal to the noise. Consider the standard errors-in-variables problem a la regression analysis; if we assume no errors in the stock returns computation as well as no correlations, the slope coefficient in (2) will be equal to one. Further, we assume that the actual return is not observable since the observable return is a combination of the real return plus some noise element. Noise may include microstructure effects such as spread components or reversible price impacts. Thus we will observe $ret_{cc} = RET_{cc} + v$ and $ret_{ck} = RET_{ck} + u$ and assume that RET_{cc} and RET_{ck} are the actual returns, and v and u have zero mean and respective variances equivalent to σ_v^2 and σ_u^2. An ordinary least squares estimation of Equation (2) will yield an estimated slope coefficient β*, where

$$\beta^* \xrightarrow{p} \beta\left(\frac{\sigma^2 RET_{ck}}{\sigma^2 RET_{ck} + \sigma_u^2}\right) \tag{3}$$

$\sigma^2 RET_{ck}$ captures the total observable information from the previous close to the time period k and σ_u^2 is the noise effect in prices at period k. The slope is thus a measure of the ratio of information content (signal) to signal plus noise in prices at period k. Therefore, the extent to which the slope is less than unity is the extent of noisiness in period k, since if there is no noise element the slope will yield one. Equation (2) is estimated for each stock and each period k. From these regressions, we obtain the slope coefficient estimates for each stock and in turn compute the mean stock slope for each time period. We also follow Biais et al. (1999) to compute the confidence bands by using the time series' standard errors of the mean of the slope coefficient estimates. The mean coefficient and estimates, along with the confidence bands, are charted in Figures 5a - 5e. As pointed out by Biais et al. (1999), the time series estimation of stock returns in the presence of learning is problematic as a result of non-stationarity, which can be induced by non-stationarity. In order to avoid the spurious regression problem, we examine each time series for unit roots using the Augmented Dickey-Fuller test; and the obtained results suggest that the variables are stationary. We also ensure that we obtain robust standard errors by applying the Newey and West (1987) heteroscedasticity and autocorrelation consistent covariance (HAC) matrix estimator, which is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. The results obtained from the HAC estimation are not materially different from those obtained for the regressions using only OLS.

INSERT FIGURE 5 ABOUT HERE

The charts for the mean coefficients are presented individually for each pound volume quintile. The charts for the lower volume quintiles are quite consistent; however, as expected, Quintile 5's chart looks slightly different. For the highest volume stocks (Quintile 5), the informational efficiency of stock prices is low prior to the call auction period when only broker-dealer trades are submitted. During the call auction interval, a dramatic rise in the mean coefficients is registered; the mean estimate increases nearly five times to 0.83 from 0.17 during the 10-minute interval ending 08:00:00hrs. 10 minutes later, at 08:10:00hrs, the mean coefficient has risen to 0.97; this level of price efficiency is thereafter largely maintained until about 09:00:00hrs. The informational efficiency of the stock prices remains high, above 0.84, for the rest of the trading day even after the market has closed. The evolution of the price discovery efficiency as shown in Figure 5 does suggest that the call auction price discovery is *informationally* efficient for the highest volume stocks. However, for lower volume stocks, which experience failure to open at the call auction, the mean coefficients at 08:00hrs are very low. The highest at 08:00hrs is for Quintile 2 at 0.23. Thereafter, however, once the continuous order-driven trading period gets under way, the mean coefficient estimates for all the lower volume stocks rise dramatically, in a fashion similar to Quintile 5's rising, during the call auction. These results are at variance with Barclay and Hendershott (2003) who report high informational efficiency in the pre-open for all stocks in their sample, although they fail to make distinctions on the basis of trading activity. Our results are however similar to Biais et al.'s (1999) findings. We put this disparity in results down to trading activity. Biais et al.'s (1999) results are based on an analysis of a market, the Paris Bourse, where no actual trading occurs during the pre-open, while Barclay and Hendershott's (2003) results are based on a sample of NASDAQ stocks traded in the pre-open with a relatively higher number of transactions than in our sample. Also in our analysis, we further divide the pre-open into five intervals before conducting our analysis, thereby yielding a reduced average number of transactions for each interval. Thus the results in this section further cement the prior literature findings that trading activity is a critical part of the price discovery process and its efficiency. The opening and closing call auctions are both *informationally* efficient for the highest volume stocks because of their adequately high level of trading activity. As shown in Table 1, the lower volume stocks also have appreciable levels of trading activities in the post-NTH, therefore their informational efficiency is largely sustained even after the market has closed, and the transaction numbers have dropped sharply. We therefore propose that if measures are introduced to increase the trading activity in the opening call for lower volume stocks, the pricing efficiency of stocks during the call auction will increase and more price discovery will shift to the opening call.

4.2.2. Weighted Price Contribution per Trade (WPCT)

The high level of price efficiency recorded for the opening call auction (10-minute period ending 08:10:00hrs) for Quintile 5 stocks (other quintiles) and the high WPCs for those periods, when considered along with the relatively low number of transactions, suggest that individual trades reveal more information for all stocks in the pre-open than during the NTH. Lower volume stocks trades during the first 10 minutes of the NTH are also expected to reveal more information than the rest of the NTH. We examine this by constructing the weighted price contribution per trade (WPCT), which measures the amount of price return observed for each of those intervals. The WPCT is computed by dividing the WPC per trading interval by the weighted ratio of trades executed during that period (interval). If, for each day, $t_{k,s}$ is the number of executed trades in time period *k* for contract *s*, and t_s is the total sum of $t_{k,s}$ for all the periods, then $WPCT_k$ is defined as:

$$WPCT_k = \frac{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right)}{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{t_{k,s}}{t_s}\right)} \tag{4}$$

Since the WPCT refers to the ratio of the aggregate price shift occurring in a period scaled by the ratio of trades in that same period, the measure should equal approximately one if all the trades contain similar information levels.

INSERT TABLE 3 ABOUT HERE

Table 3 reports the results for the WPCT analysis. As hypothesised, trades in the pre-open are very informative and are all significantly different from zero. Given that most of the price discovery per minute occurs between 08:00and 08:10hrs for the lower quintile stocks, WPCTs are also high and significantly different from zero for that period and for those stocks. Generally the WPCTs are very high, and somewhat noisy given the low trading levels, prior to the open. Thereafter they decline as the NTH commences. This shows that the informativeness of individual transactions has dwindled, and that during the NTH one trade hardly moves prices in a significant manner; i.e. price movements are likely to occur on account of order flow rather than just a trade (see for example Chordia et al., 2008). The results in this section are further confirmation that the market is more efficient during the NTH than other trading periods, since it is unlikely that one trade's information content will be large enough to cause a significant shift in price. Also, the trades have become less disproportionately informative than they seem to be during the pre-open. Further, the results here, considered in tandem with the increasing liquidity evidenced in the spread analysis shown in Figures 5a and 5b, suggest that as the market progresses from the opening call auction period towards the NTH the stock prices, especially for large volume stocks, become more efficient.

We contend that the improvement in stock price efficiency in the case of Quintile 5 stocks during the opening call is a function of the informativeness of the transactions. As the day progresses, trades become less informative after the information accumulated at the previous day's close has been incorporated in the early trading, starting with the opening call auction for the Quintile 5 stocks. Had the lower quintile stocks been able to muster trading depth during the call, their price discovery would have commenced earlier, at the open call auction, as well. However, given a fear of lack of counterparty to fill orders, many lower volume stock traders opt to either hold off trading until the floor opens at 08:00:00hrs, or trade through the broker-dealer route. Trading activity evidence suggests that the majority of this class of traders do the former. Thus, based on the data in our sample, lower volume stock traders are not really choosing between the broker-dealer route and the call auction as suggested by Ellul et al. (2005). Rather they are largely withholding trades until the market opens, where they are more likely to have their orders filled, or perhaps to avoid trading in an environment dominated by informed traders. Since lower volume stock traders are likely to be largely uninformed or noise traders, they will normally avoid trading with informed traders or seek a premium for doing so. This view is underscored by recent theoretical evidence presented by Malinova and Park (2014). They show that in a dynamic market where several heterogeneously informed traders choose to place orders, better informed traders trade immediately, while worse informed traders delay even when they know that the market could move against them. We therefore suggest that small volume stock traders avoid trading during the call auction because of the dominant presence of informed traders, thereby leading to the failure of lower volume stocks at the opening call auction. In Section 4.3, we examine the evolution of informed trading/information asymmetry across the different trading periods. If the opening call period has higher adverse selection costs than other trading periods, this will support our hypothesis. Based on the evolution of the spread estimates in Figure 4, we expect a higher level of informed trading during the opening call auction period. The pre-open and post-NTH spreads are generally wider than the NTH. Even more surprising is the sustained widening of spreads during the opening call auction period for mainly the highest volume stocks. For example, the bid-ask (effective) spread increases more than 43 (17) times at the opening call auction start (07:51:00hrs) from the previous minute. This unexpected evolution however resonates with the relative and uneven informativeness of the high volume stock trades during the entire pre-open period. Curiously, the relative informativeness of the opening call auction trades help in raising the level of price efficiency despite their widening of the spreads because they are information-driven trades. Thus the new prices they reveal are unlikely to be reversed in the short term. The spreads are therefore wider during the opening call auction period because market makers recognise the impact of the auction transactions and respond accordingly. The informativeness of the transactions is evidenced further by the rapid improvement in price efficiency starting at 07:51:00hrs.

INSERT TABLE 3 ABOUT HERE

4.3. Modelling Adverse Selection Costs

4.3.1. Adverse Selection Costs by Trading Pressure

We now return to the question of the type of traders dominating trades at specific intervals during the trading day. Early microstructure models identify two main types of traders: the liquidity trader, who trade in order to maintain an optimal portfolio, and the informed trader, whose aim is to profit from private information. Low volume stock traders are likely to avoid trading in an environment dominated by informed traders, because they are uninformed themselves and are thus largely liquidity traders. Given the evolution of the various spread measures obtained across the day (see Figure 4), there is sufficient reason to expect that the relative composition of traders evolves quite significantly from period to period. Since the spreads are higher in the pre-open and post-NTH, we expect the trades during those periods to be of the informed variety. As trading periods dominated by informed traders are characterised by higher adverse selection costs, the spreads widen to accommodate increasing market makers' adverse selection costs in addition to other costs captured by the spread – stationary inventory and transaction costs.

We estimate the adverse selection costs using the Huang and Stoll (1997) spread decomposition model; we expect this to give us an indication of the type of traders dominating different points across the trading day. This approach employs the fact that quote shifts due to inventory costs do not arise from inventory alterations in just one stock, i.e. the instrument of interest, but from other stocks held in a given portfolio of stocks.[13] This is thus a portfolio approach to decomposing the spread, it is based on the assumption that adverse information relates to instruments on an individual basis, yet inventory impacts are portfolio wide. In employing this approach, we assume, similarly to Heflin and Shaw (2000), that 'liquidity suppliers'/market makers take the opposite of all executed trades or submitted call auction orders, which are then executed when the call algorithm runs. Liquidity providers may not be interpreted strictly as market makers, but also as other traders watching more than just one stock at a time. This is tenable since liquidity may be defined as the availability of counterparties to trade with. Indeed Huang and Stoll (1997) propose a refinement of their

[13] Consider a liquidity supplier purchasing stock x at the bid quote. The trade will lower the bid and offer prices of the stock as well as for other correlated stocks. The opposite of this trade is a sale in the correlated stocks; this hedges his position in stock x. In reverse, if we assume that the other stocks are constrained by trading pressure, the liquidity supplier may choose not to induce lowering of the quoted prices for x if his aim is to hedge his buying of other stocks thus spurring sales in x. This approach recognises that there is a probability that x's quotes are driven by more than just inventory impacts and the information components of only x. Specifically, trading pressure on account of other stocks should result in alterations in quotes of x due to the efforts of liquidity suppliers to retain the balance of their portfolios.

approach through the nomination of specific portfolios other than purely a market maker's. An example of such a portfolio is an index portfolio such as the FTSE 100, which we employ in this paper.

The Huang and Stoll (1997) spread decomposition model[14] is given as:

$$\Delta P_{k,t} = \beta_{1,k} Q_{k,t} + \beta_{2,k} Q_{k,t-1} + \beta_{3,k} Q_{A,t-1} + e_t, \tag{5}$$

where $\Delta P_{k,t}$ is the change in price from the previous retained trade, $Q_{k,t}$ is equal to 1 (-1) when the transaction at period t for stock k is a market maker sell (buy) and $Q_{A,t-1}$ is the aggregate buy-sell indicator variable used to encapsulate portfolio trading pressure on market makers' inventory levels, defined for a portfolio of n stocks as:

$$\begin{aligned} Q_{A,t-1} &= 1 \, for \sum_{k=1}^{n} Q_{k,t-1} > 0 \\ Q_{A,t-1} &= -1 \, for \sum_{k=1}^{n} Q_{k,t-1} < 0, \\ Q_{A,t-1} &= 0 \, for \sum_{k=1}^{n} Q_{k,t-1} = 0 \end{aligned} \tag{6}$$

As the original datasets do not include information on trade direction, we employ Lee and Ready's (1991) algorithm to determine the direction of trade. Specifically, we classify trades at a price above the prevailing quote midpoint as market maker sells, and those at a price lower than the prevailing quote midpoint as market maker buys. If the current and the previous trades are the same price, we classify using the next previous trade. This algorithm is established in microstructure literature. Further, independent analysis by Aitken and Frino (1996) supports Lee and Ready's (1991) suggestion that the algorithm's accuracy exceeds 90%. The adverse selection spread component, and the half spread, are thus computed by estimating Equation (13) using LS as adopted by Heflin and Shaw (2000); the $\beta_{1,k}$ estimate is

[14] This approach is also related to the Ho and Stoll (1983) model that shows the connection between quote adjustments in a stock and inventory changes in others. They show that the quote shifts in stock a in reaction to a trade in another stock b is dependent on $cov(R_a, R_b)/\sigma^2(R_b)$.

one-half the estimated effective spread, and the adverse selection component is equivalent to $2(\beta_{2,k} + \beta_{1,k})$.[15] This approach is established in the literature, (see Heflin and Shaw, 2000; Van Ness et al., 2001). Van Ness et al. (2001) even suggest that the Huang and Stoll (1997) approach is superior to other commonly used models in measuring adverse selection information costs. However, this seeming superiority comes at a cost. The possibility of obtaining implausible estimates from the model estimation when using the probability of trade reversal approach, rather than the trading pressure approach, has been reported. For example, Clarke and Shastri (2000) report this problem in their analysis of 320 NYSE firms; Van Ness et al. (2001) also report similar issues. There seems to be a correlation between reduced probability of trade reversal and the implausible estimates. This paper reports only the trade aggregator estimation, and there is no suggestion that we are faced with this problem. Also it is necessary to align the trading times across all stocks involved in the estimation. This paper follows an approach described by Huang and Stoll (1997); specifically, we employ only the last trade at every five-minute interval when formulating our variables.[16] Huang and Stoll (1997) stated that a cross-sectional estimation of Equation (13) is likely to lead to an overestimation of the adverse selection costs. We avoid this potential anomaly by adopting time series estimation.[17] We use the Wilcoxon-Mann-Whitney test for

[15] Equation (13) can also be estimated using the GMM procedure with appropriate adjustments to the orthogonality conditions. The GMM levies relatively weak distributional requirements unlike maximum likelihood (see Huang and Stoll, 1997; Madhavan et al., 1997). In addition to following Heflin and Shaw's (2000) estimation approach, we also estimate using the Newey and West (1987) HAC.

[16] Huang and Stoll (1997) observe that big orders are sometimes broken into smaller trades (see also Barclay and Warner, 1993; Chakravarty, 2001). To account for the associated problems arising from this practice, they devise a 'bunching' technique, such that trades executed at the same price, with same quotes and within five-minute intervals of one another are bunched into one trade and treated as such. They however conclude that using one trade every five minutes greatly reduces any problem that may arise from breaking up large orders. Heflin and Shaw (2000) also adopt this approach. Moreover the results obtained by Huang and Stoll (1997) utilising the bunching technique suggest that the method unnecessarily increases the adverse selection component estimates.

[17] We also employ panel GMM estimation. Although this method led to the loss of many observations in order to ensure *synchronity*, the overall trend of the evolution of adverse selection costs is consistent with the time series averages.

obtaining statistical inference on the differences between NTH intervals and the corresponding pre-open or post-NTH periods.

INSERT TABLE 4 ABOUT HERE

Table 4 presents the cross-sectional mean of the adverse selection costs by time period and pound volume quintile. The opening call auction adverse selection costs for lower volume stocks could not be obtained because of the very low number of trades over the sample period. Given that we could not robustly estimate their values with our chosen model, we report adverse selection costs for only the highest volume stocks. The available results however support our hypothesis that the opening call auction period for the highest volume stocks has a significantly higher level of informed trading than other trading periods across the day. The results also show that informed trading is lowest during the NTH, while the pre-open and post-NTH periods generally have higher levels of informed trading across all quintiles. Adverse selection costs are lowest across the trading periods for Quintile 2 stocks; the pre-opening auction (closing auction) adverse selection costs is 14 (6) times the value for the NTH. Overall, there is higher level of informed trading recorded for the higher volume stocks during the pre-open and post-NTH, however during the NTH, the lowest pound volume stocks (Quintile 1) post the highest adverse selection costs. For completeness, we also estimate daily order imbalance (OIB) measures as in Chordia et al. (2008) for each of the trading intervals.[18] The results obtained show that the opening call auction period is highly informative for only the highest trading stocks even when dealer trades are considered. This is underscored by the significantly positive values for the period in the case of the highest volume stocks. For example, the nominal (pound) OIB is highest for Quintile 5 stocks during the opening call auction at 0.292 (0.384) and lowest for Quintile 2 stocks during the NTH at -

[18] We thank the referee for suggesting this. For brevity, the full results are not presented in this draft but are available on request.

0.003 (-0.009). In confirmation of the order flow variation across the day most non-NTH OIB values are significantly different from corresponding NTH OIB values.

With these results, our expectation that the opening auction, and generally the pre-open, contain higher levels of informed trading is therefore confirmed. Thus our results contradict previous submissions from theoretical and experimental studies, which suggest that call auctions lead to lower information asymmetry (see for example Madhavan, 1992; Schnitzlein, 1996). Given, the significance of the results obtained, we propose that the lack of trading for lower volume stocks during the opening call auction is related to the significantly higher presence of informed traders during the period. This is further strengthened by the fact that for lower volume stocks, more dealer trades are recorded per minute for the 40-minute period prior to the opening call auction, than for the call auction period. This suggests that unless a more transparent opening call auction market is ensured, even when there is a higher level of potential counter parties for lower volume stock traders, they are unlikely to engage with the opening call auction.

5. Conclusion

The opening and closing prices are important reference points for investors and the general public. Opening prices may affect trader sentiment throughout the day, and closing prices may be used to settle derivative contracts. Our results, however, suggest that the opening call auction often fails, and, on average, the pre-open incorporates little of the overnight information for low volume stocks. This may have repercussions for the value of investor portfolios – whether these portfolios are composed of the stock itself or a derivative of the stock. Based on the foregoing, we examine whether the opening and closing prices yielded by the call auction mechanism on the LSE are *informationally* efficient. We find very large variability in our results with respect to trading volumes, such that higher volume stocks are more likely to be traded during the opening call auction than lower volume stocks. In fact lower volume stocks routinely fail at the opening call auction. Results suggest that this is due to both the unavailability of trading counterparties, as well as a conscious decision by lower volume stock traders to avoid the opening call auction given the domination of the period by informed traders. Although Ellul et al. (2005) suggest that lower volume stock traders opt for the dealer market during the opening call auction because of lack of trading partners; we find very little evidence to support this. Rather, lower volume stock traders generally abstain from any form of trading during the 10-minute opening auction period. Thus, the price discovery process mainly commences for those stocks after the market opens, with more than 30% of the daily close-to-close price discovery occurring within the first 10 minutes of the market opening. For the higher volume stocks however, the highest rate of price discovery (31.8% over 10 minutes) occurs during the opening call auction period. Given the distribution of price discovery across the day, the opening call auction period yields a highly *informationally* efficient opening price for higher volume stocks, while an efficient price is not obtained for lower volume stocks until within the opening 10 minutes of the NTH. So inefficient is the price yielded during the call auction period for lower volume stocks, that informational efficiency is generally higher in the 30 minutes prior to the opening call auction than during it.

The closing price yielded by the closing call auction for all stocks is however better behaved and highly *informationally* efficient. This is because the NTH is a very efficient trading period, thus providing a strong price discovery platform for the closing auction and the immediate market period afterwards (post-NTH). The results relating to the closing call auction are therefore consistent with previous literature (see for example Chelley-Steeley, 2008). However, having examined the LSE's microstructure, we find no evidence that the closing call auction market quality characteristics impact on the next day's early trading as suggested by Chelley-Steeley (2009). If this were the case, price discovery and its efficiency would be high in the pre-open, especially for low volume stocks. Further, we document an interesting phenomenon, which runs contrary to Amihud et al.'s (1990) observation on the Milan exchange. We show that the call auction preceded by continuous trading leads to enhanced price discovery and efficiency for low volume stock rather than otherwise.

Generally, the results in this study suggest that the influence of the call auction for opening the market might have been exaggerated and oversold to investors by platforms eager to please the markets. According to Madhavan (1992), the advantage of a call auction comes from two offerings: transparency, because all orders are released to the market as at when placed, and higher liquidity, because all orders are in before auction. However, in an era where high frequency trading is increasingly pre-eminent, these 'advantages' can no longer be considered as such because higher volumes of trading are achieved during the NTH, and the order book, on the LSE for example, is regularly updated in a fashion that allows for comparable transparency as during the call auction. Our results suggest that the LSE pre-open does not yield *informationally* efficient prices for low volume stocks, and that only high volume stocks benefit from price discovery efficiency during the opening call auction. We however believe that the opening call auction could be made more transparent and lower volume stock-friendly if the exchange de-emphasises volume during the opening call. The call auction algorithm executes with the aim of maximising volume, and this means that trades may not be executed at the best possible prices from an uninformed trader's point of view. We propose that the exchange prioritises prices instead, and aim for executing at a volume weighted price during the opening call auction, while moving all unexecuted orders on to the order book for trading during the NTH. The call auction algorithm should include appropriate circuit breakers. If this does not improve the lower volume stock participation, this paper has shown sufficient evidence suggesting that doing away with the opening call auction altogether will not diminish the efficiency of the opening reference price.

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Figure 1: Daily Trading Volume per Minute for FTSE 100 Stocks

The average pound daily volume is computed for each minute and for each quintile. The logs of the quintile values are graphed due to the large variability of trading volumes across different trading periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

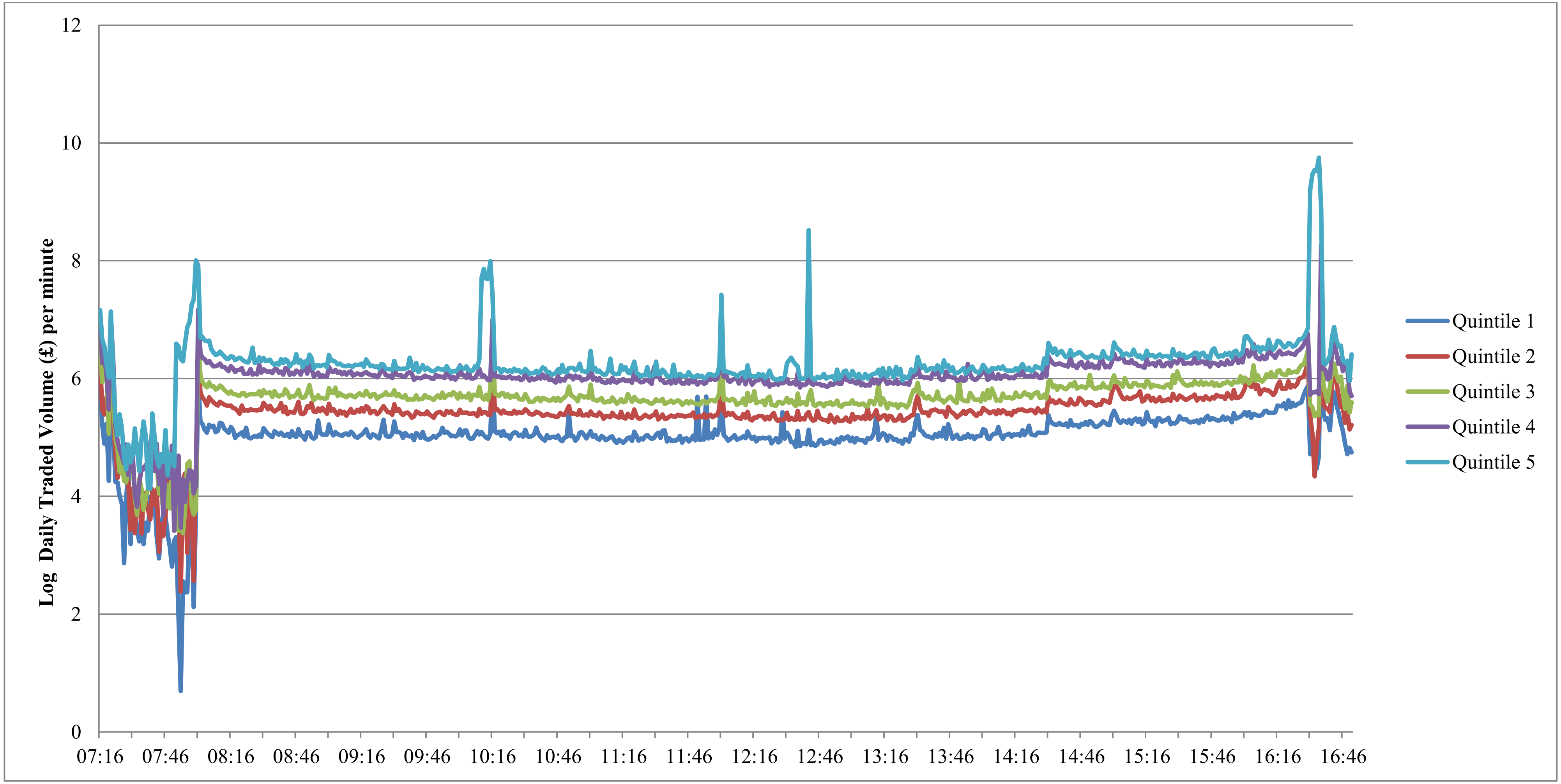


Figure 2: Mean Trade Size per Minute across Quintiles

The mean trade sizes per minute are computed for each quintile. The logs of the mean estimates are graphed due to the large variability of trading volumes across the three periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

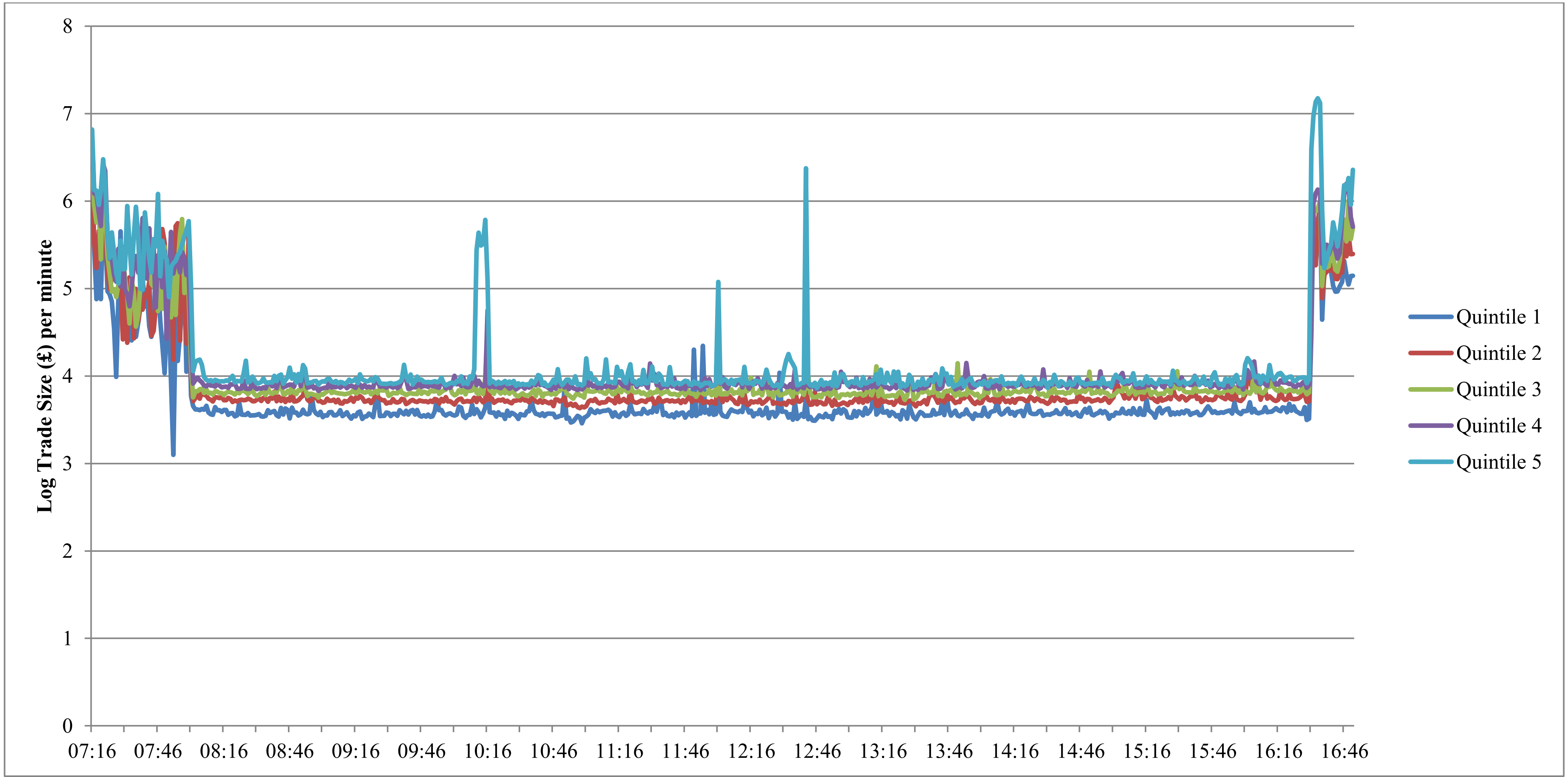


Figure 3: Median Trade Size per Minute across Quintiles

The median trade sizes per minute are computed for each quintile. The logs of the median estimates are graphed due to the large variability of trading volumes across the three periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

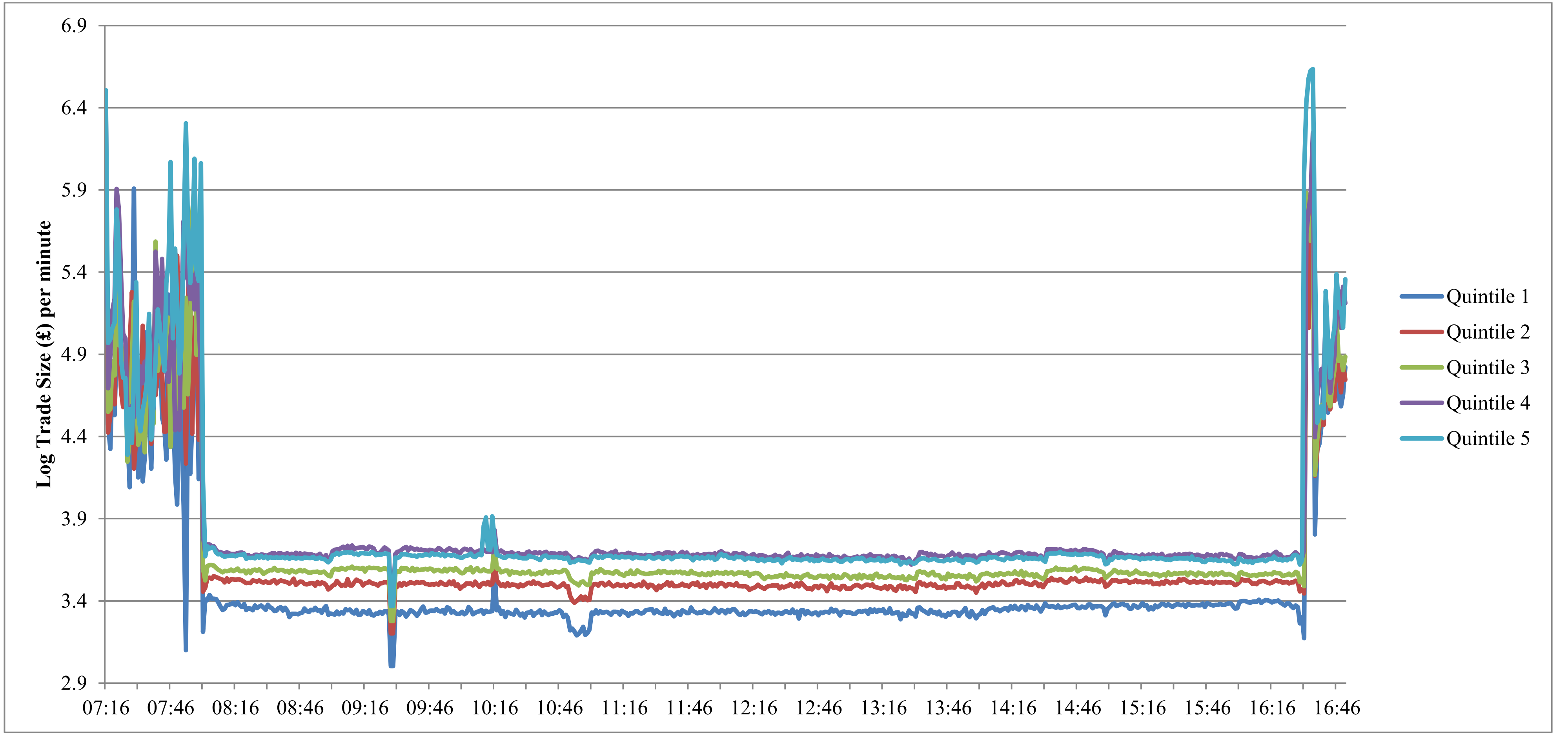


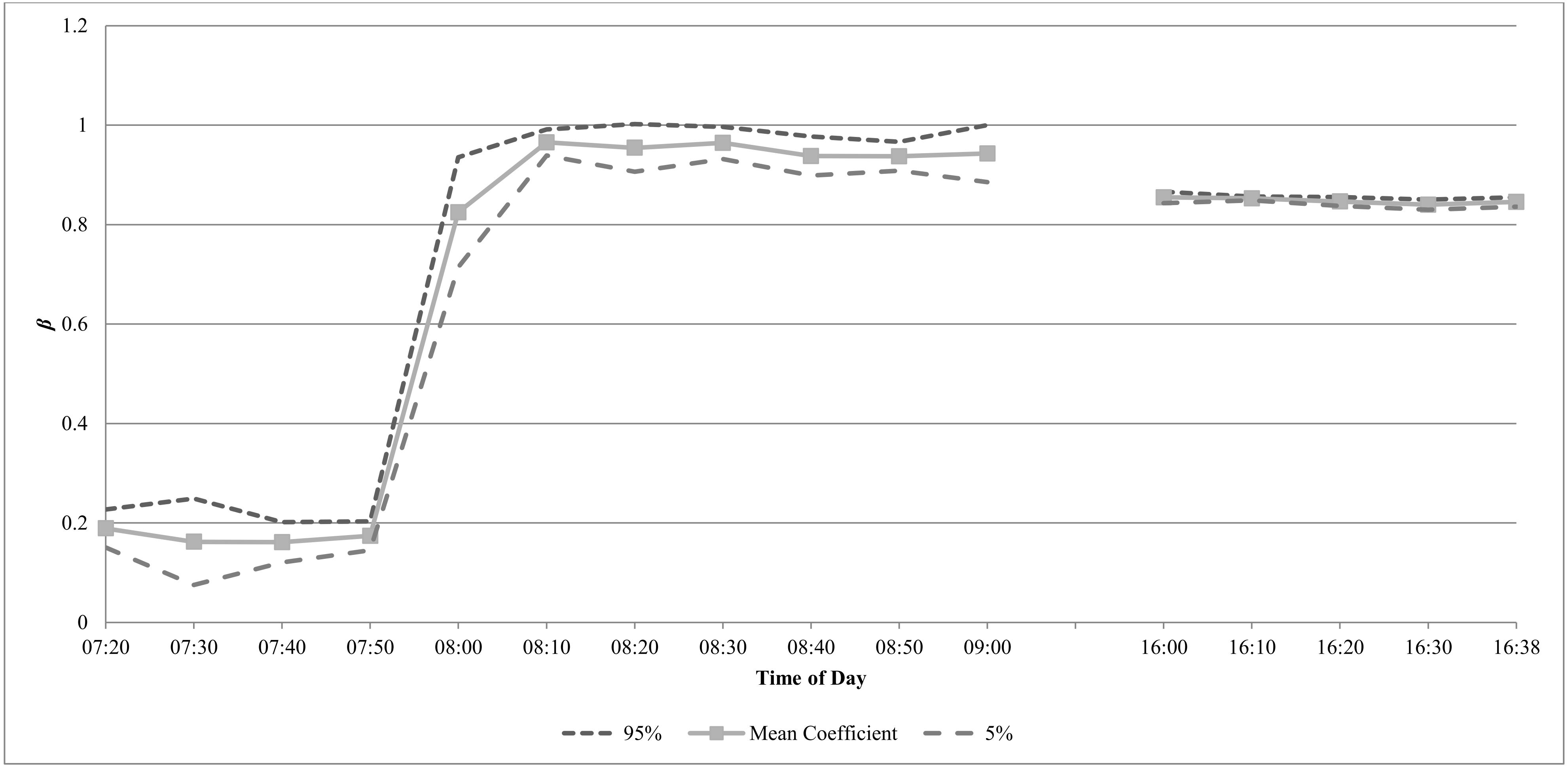
Figure 4 Informational Efficiency by Time periods

The signal:noise ratio is computed for 10 minute intervals by regressing close-to-close return on the return from close to time period, *k* for FTSE 100 stocks trading between 1st October 2012 and 30th September 2013. For each stock, the following equation is estimated separately for each time interval where ret_{cc} is the close-to-close return and ret_{ck} is the return from the close to the end time of period *k*:

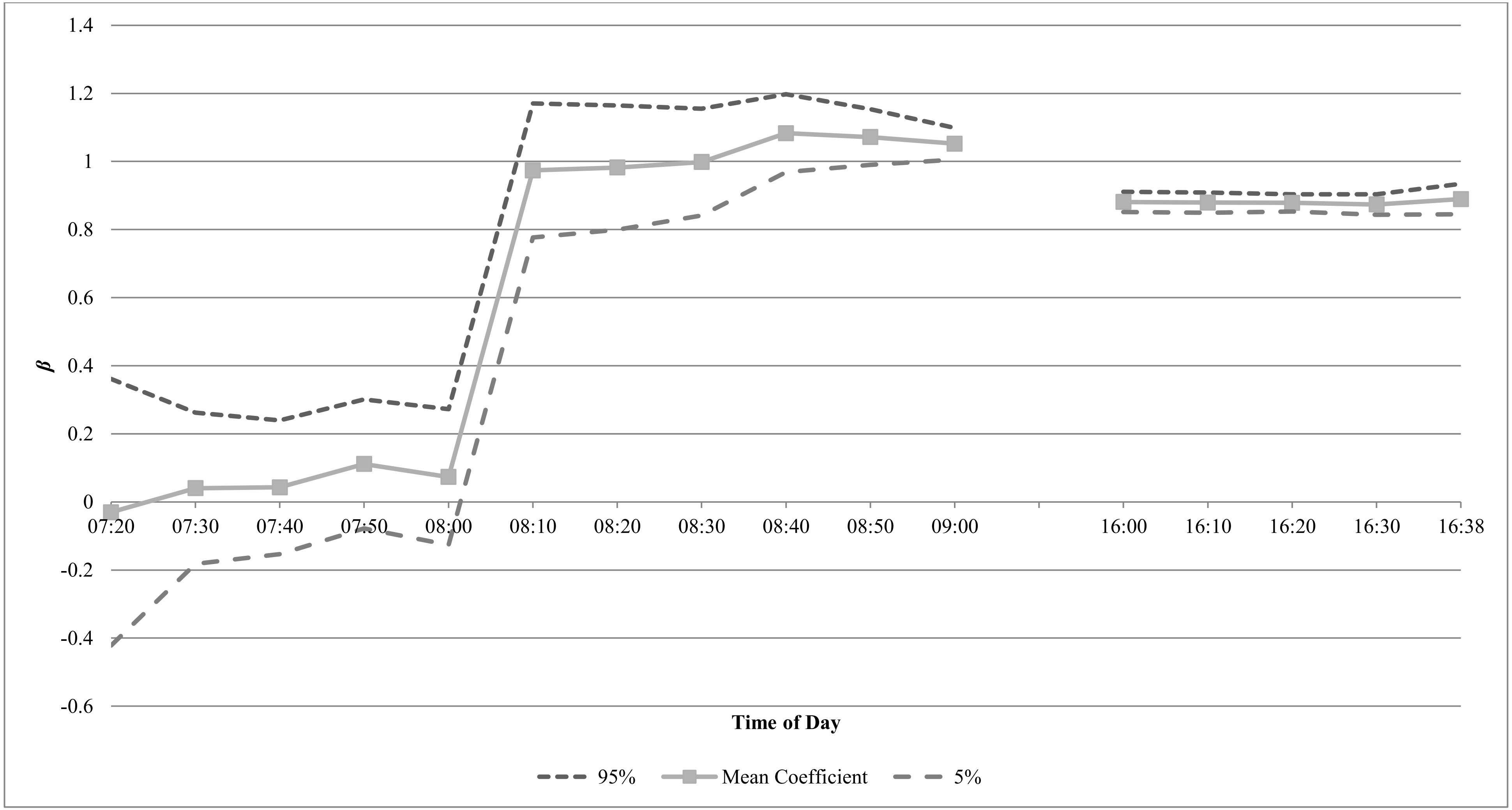
$$ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k$$

Mean value of the coefficient estimates are obtained for each quintile in the sample and sub-figures A to E graph the informational efficiency as measured by the signa:noise ratio per interval for each of those five quintiles. Confidence intervals are computed by employing the time series standard errors of the mean of the coefficient estimates.

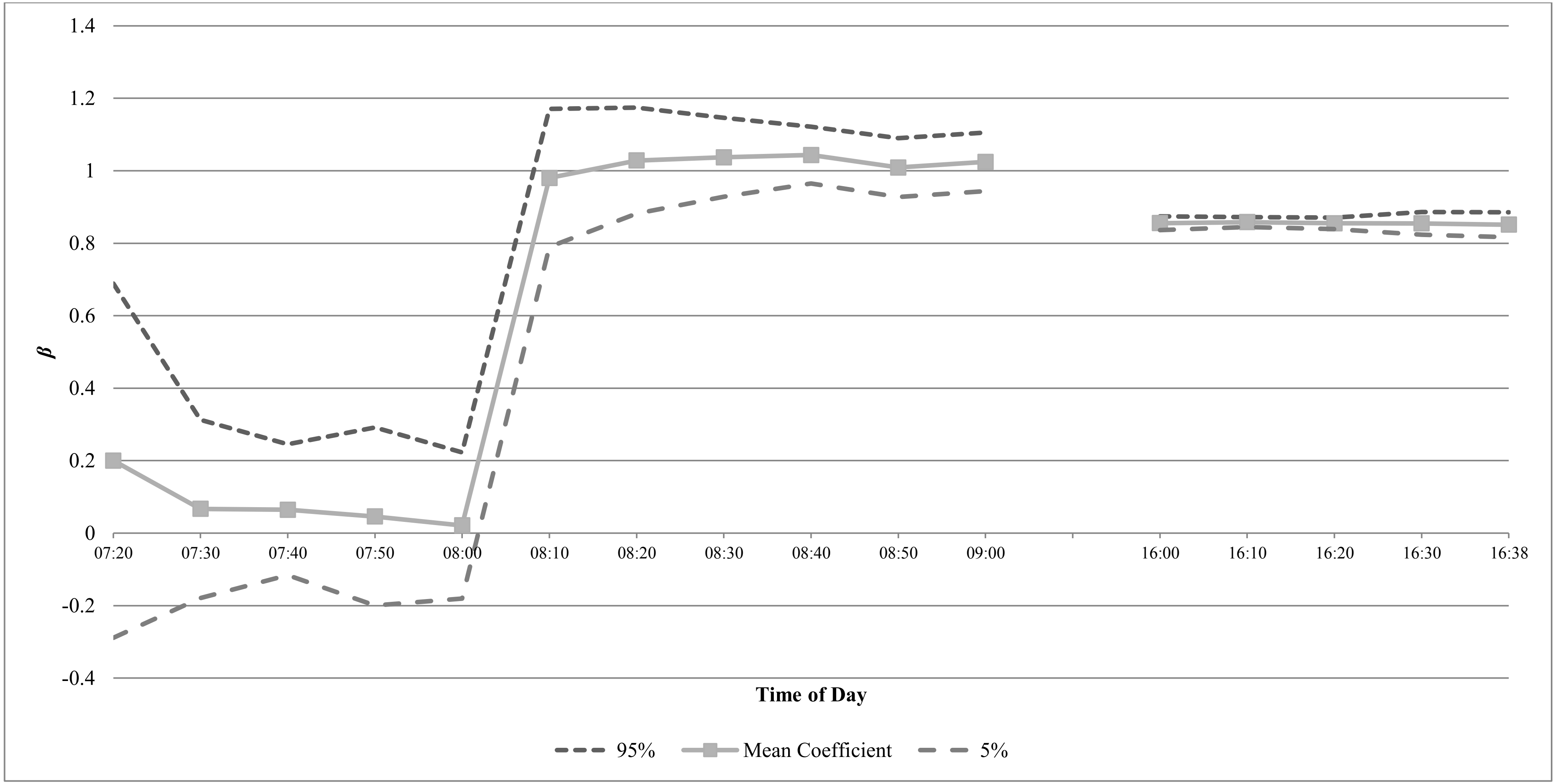
A: Quintile 5 Stocks (Highest)



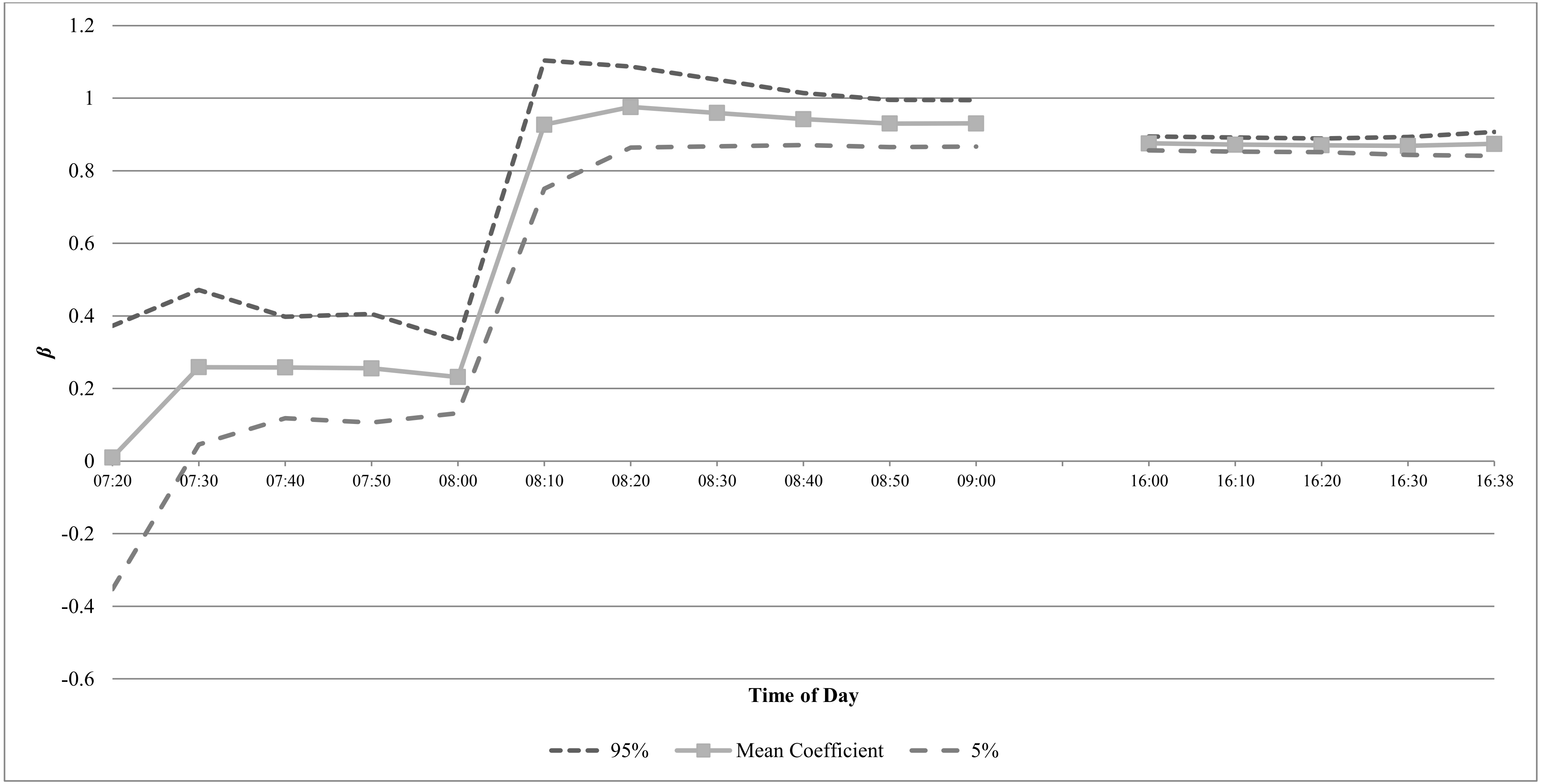
B: Quintile 4 Stocks



C: Quintile 3 Stocks



D: Quintile 2 Stocks



E: Quintile 1 Stocks (Lowest)

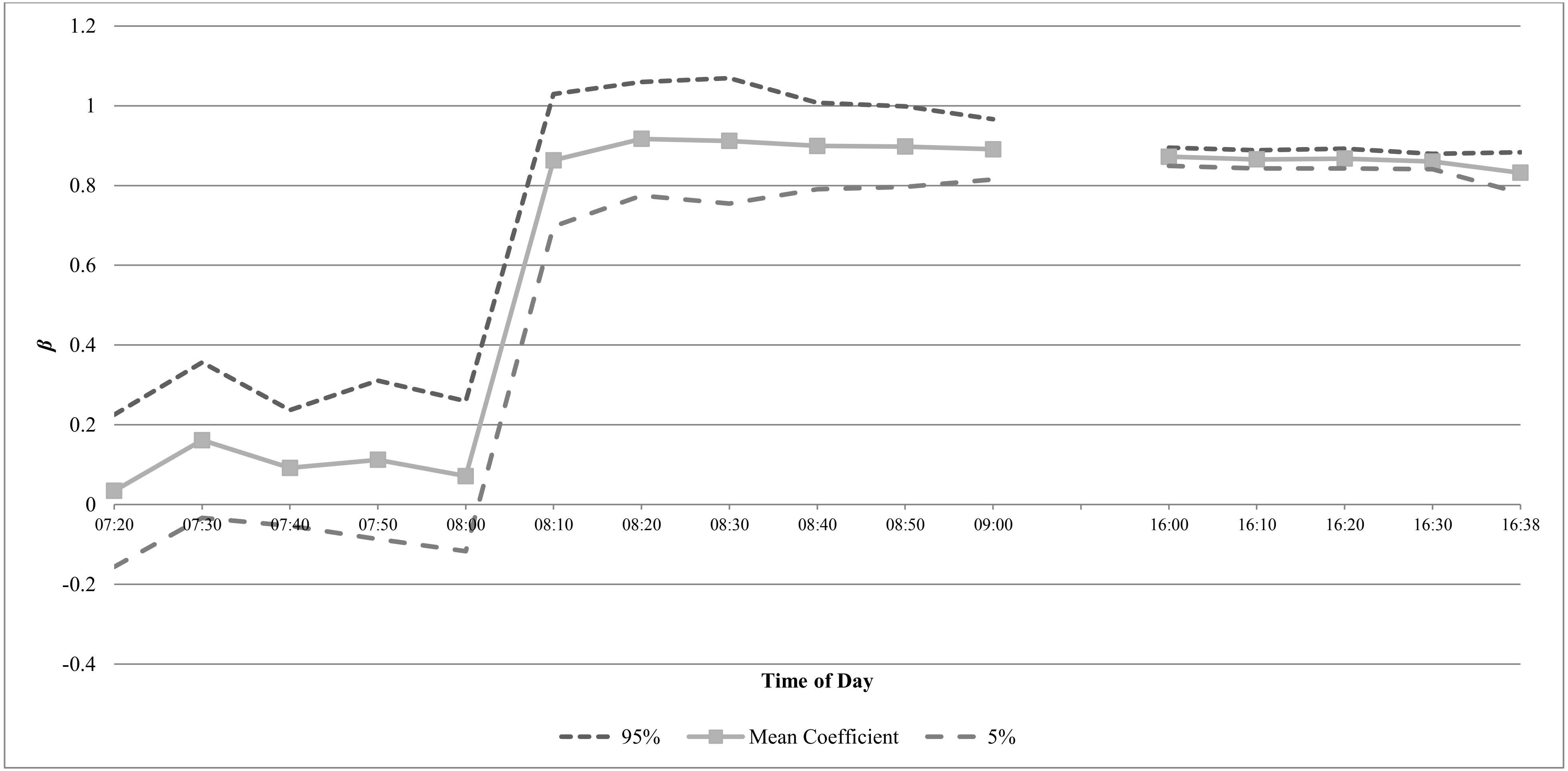
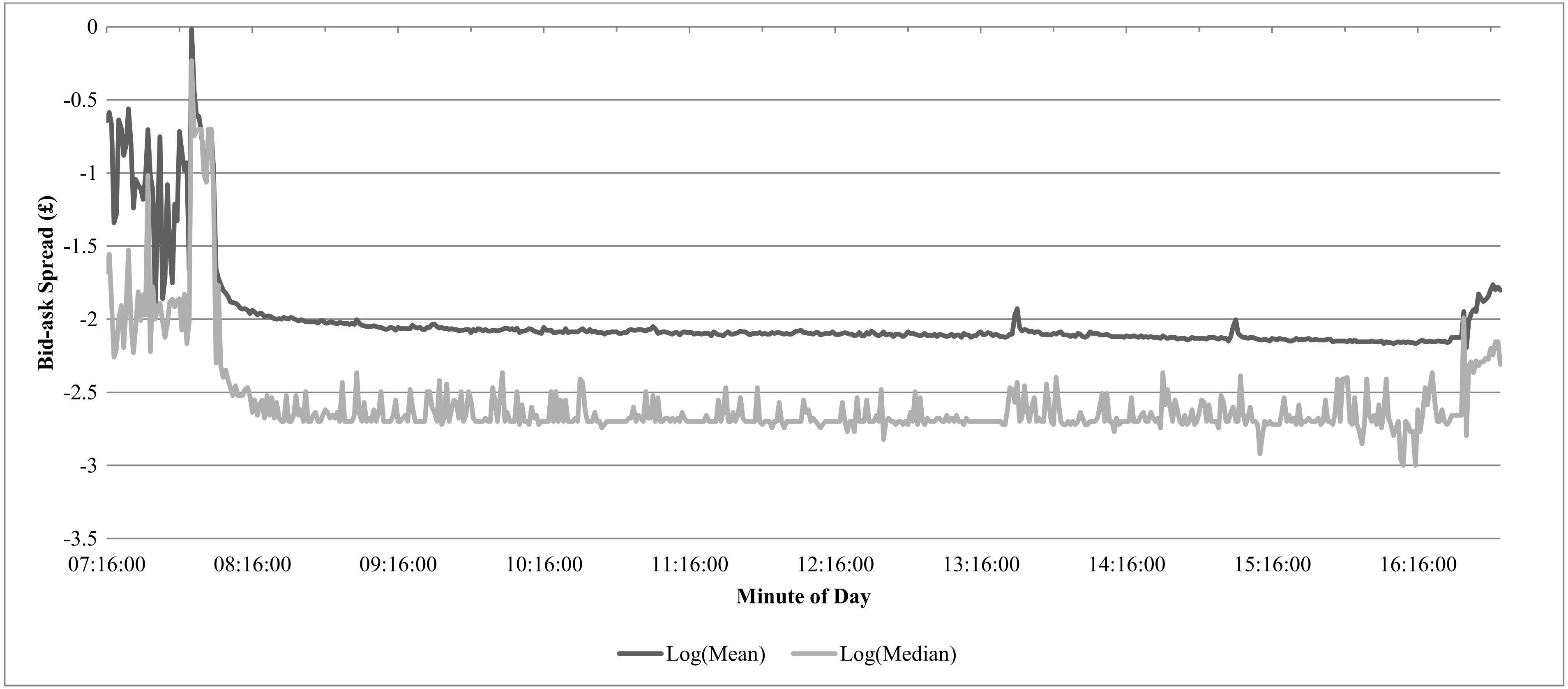


Figure 5: Liquidity by Time Periods for FTSE 100 Stocks

Liquidity proxies per minute are computed for FTSE 100 Stocks trading between 1st October 2012 and 30th September 2013. Figure A shows the Quoted Bid-Ask spread, measured as the difference between the best ask and the best bid price, while Figure B shows the Effective Spread, measured as twice the absolute value of the difference between the best trade price and prevailing midpoint per minute. The logs of the spread estimates are graphed because of the large variability of spreads across the trading periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

A: Quoted Bid-Ask Spread



B: Effective Spread

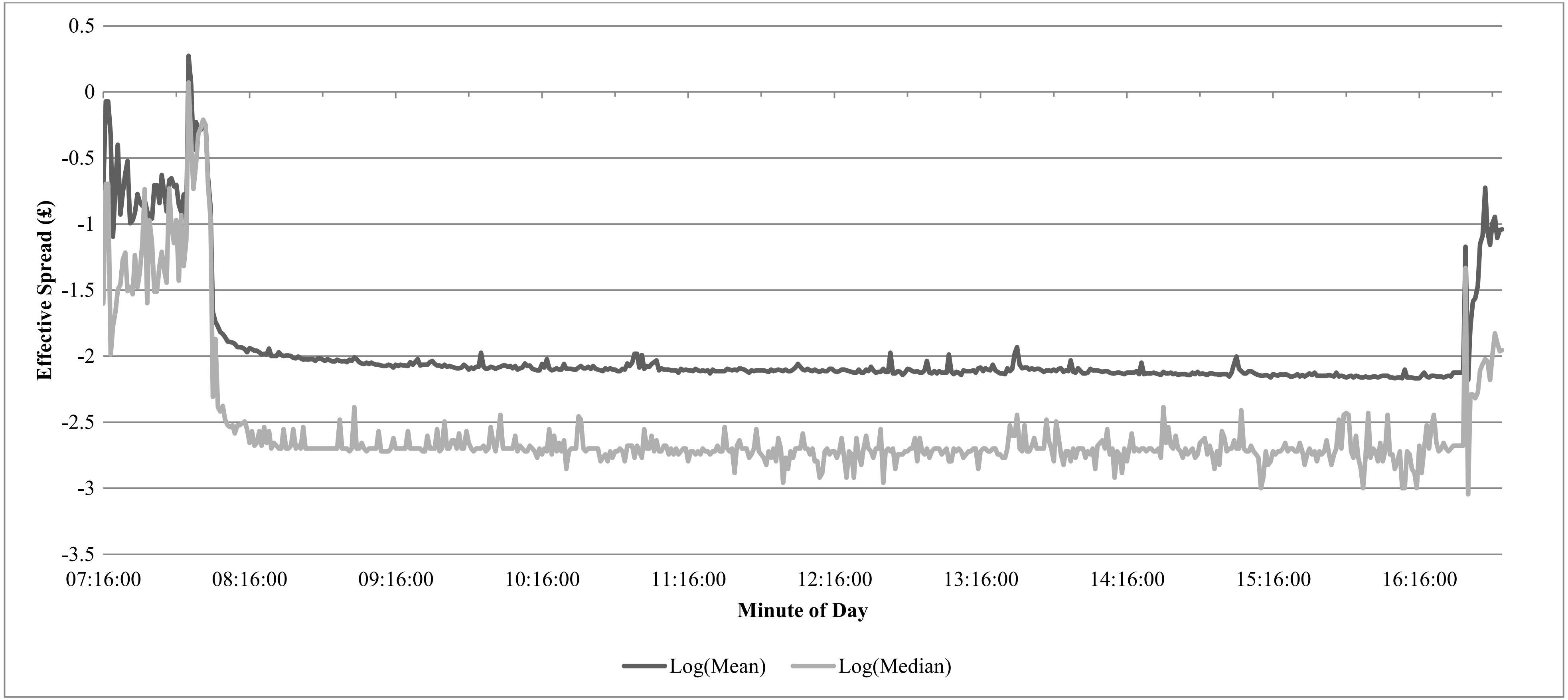


Table 1: Summary Statistics for FTSE 100 Stocks

The table shows the daily trading activity statistics for 70 FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013. Panels A and B present summaries for the trades executed directly via the Stock Exchange Electronic Trading System (SETS) on the exchange floor and the parallel dealer market respectively, while Panel C shows daily averages of the transactions for both venues. In all panels, the sample stocks are ranked by pound volume into quintiles. Quintile 5 contains the 14 highest trading stocks by daily pound value, and Quintile 1 contains the 14 least traded stocks by daily pound value. The panels are divided into three main time periods for each quintile: Pre-open (07:10:00hrs - call end), NTH (08:00:30hrs - 16:30:00hrs) and Post-NTH (16:30:01hrs - 16:50:00hrs). Pre-open is also further divided into Pre-opening call auction (07:10:00hrs - 07:50:00hrs) and the Opening auction (07:50:01hrs - call end). Post-NTH also includes the Closing auction (16:30:01hrs - 16:38:00hrs) and the Post-close (16:38:01hrs -16:50:00hrs).

Panel A**:** Exchange Floor Trades Daily Trading Summary

	Number of Transactions					**Volume (£'000,000)**				
	Pre-Open			**Post-NTH**		**Pre-Open**			**Post-NTH**	
Pound Volume Quintile	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)	Normal Trading Hours (NTH) (08:00:01-16:30)	Closing Auction (16:30:01-16:38)	Post-Closing Auction (16:38:01-16:50)	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)	Normal Trading Hours (NTH) (08:00:01-16:30)	Closing Auction (16:30:01-16:38)	Post-Closing Auction (16:38:01-16:50)
Highest	0.00	426.92	98333.12	2623.41	10.84	0.00	171.70	1171.40	17836.59	0.43
4	0.00	0.00	77227.34	956.01	3.60	0.00	0.00	554.01	183.60	0.18
3	0.00	0.00	40726.37	786.09	1.56	0.00	0.00	240.61	83.53	0.07
2	0.00	0.00	28360.21	670.68	1.23	0.00	0.00	136.47	51.94	0.10
Lowest	0.00	0.00	17390.17	565.62	0.50	0.00	0.00	58.20	24.90	0.01
Overall	0.00	426.92	262037.20	5601.82	17.72	0.00	171.70	2160.69	18180.57	0.79

Panel B: Dealer Trades Daily Trading Summary

	Number of Transactions					Volume (£'000,000)				
	Pre-Open		Normal Trading Hours (NTH) (08:00:01-16:30)	Post-NTH		Pre-Open		Normal Trading Hours (NTH) (08:00:01-16:30)	Post-NTH	
Pound Volume Quintile	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)		Closing Auction (16:30:01-16:38)	Post-Closing Auction (16:38:01-16:50)	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)		Closing Auction (16:30:01-16:38)	Post-Closing Auction (16:38:01-16:50)
Highest	23.45	1.32	7382.11	29.36	64.43	42.85	1.16	552.98	10.13	37.71
4	18.83	0.90	7115.34	25.01	53.94	32.02	0.19	154.91	6.83	21.09
3	14.75	0.61	4387.65	17.36	38.10	13.75	0.13	70.48	3.49	9.69
2	10.89	0.48	2616.66	11.26	31.48	5.38	0.13	37.28	1.44	5.29
Lowest	7.37	0.23	1008.97	6.86	22.04	2.46	0.02	14.99	0.84	2.49
Overall	75.300	3.542	22510.719	89.846	210.000	96.452	1.627	830.642	22.722	76.265

Panel C: Average Pound Trade Sizes

	Floor Trades					Mean ('000)				
	Pre-Open		**Normal Trading Hours (NTH) (08:00:01-16:30)**	Post-NTH		Pre-Open		**Normal Trading Hours (NTH) (08:00:01-16:30)**	Post-NTH	
Pound Volume Quintile	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)		Closing Auction (16:30:01-16:38)	Post-Closing Auction (16:38:01-16:50)	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)		Closing Auction (16:30:01-16:38)	Post-Closing Auction (16:38:01-16:50)
Highest	-	402.19	11.91	6799.01	39.27	1826.79	879.89	74.91	344.96	585.21
4	-	-	7.17	192.05	49.44	1700.39	215.52	21.77	272.99	390.87
3	-	-	5.91	106.27	43.70	931.82	208.57	16.06	201.18	254.26
2	-	-	4.81	77.44	81.91	494.02	266.93	14.25	127.81	168.16
Lowest	-	-	3.35	44.02	27.34	333.54	65.98	14.86	121.79	112.97
Overall	-	402.19	8.25	3245.48	44.34	1280.90	459.30	36.90	252.90	363.17

Table 2: Price Discovery by Time Period for FTSE 100 Stocks

The Weighted Price Contribution (WPC) is computed by the pound volume quintile for FTSE 100 stocks. For each trading session/day and period *k*, we define the WPC as:

$$WPC_k = \sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right),$$

ret_s corresponds to the close-to-close return for stock *s* and $ret_{k,s}$ is the log-return for period *k* and for stock *s*. The final row shows the fraction of days with their close-to-close return equalling 0. Mean WPCs are obtained for each day and the time series standard error of the daily WPCs used for statistical inference. * indicates the WPCs, which are significantly different from 0 at 0.01 level. The data covers the trading period between 1st October 2012 and 30th September 2013.

		Pound Volume Quintile	Highest	4th	3rd	2nd	Lowest	Overall
Time Periods	Pre-Open/Opening Auction	07:10 - 07:20	0.009	0.086	0.041	-0.026	-0.024	0.017
		07:20 - 07:30	0.029	-0.005	0.014	0.096	0.046	0.031
		07:30 - 07:40	0.002	-0.013	0.016	-0.072	-0.005	-0.014
		07:40 - 07:50	0.016	0.017	-0.012	0.006	0.011	0.007
		07:50 - 08:00	0.318*	0.004	0.004	-0.001	-0.001	0.065
	Open-Close/NTH	08:00 - 08:10	0.068*	0.286*	0.424*	0.369*	0.369*	0.303*
		08:10 - 08:20	0.056*	0.076*	0.048*	0.069*	0.071*	0.064*
		08:20 - 08:30	0.034*	0.021	0.037*	0.042*	0.033*	0.033*
		08:30 - 08:40	0.054*	0.019	0.033*	0.047*	0.027*	0.036*
		08:40 - 08: 50	0.030*	0.028*	0.031*	0.042*	0.032*	0.033*
		08:50 - 09:00	0.024	0.005	0.029*	0.031*	0.005	0.019*
		09:00 - 16:00	0.350*	0.465*	0.406*	0.417*	0.460*	0.420*
	Closing Auction/Post Close	16:00 - 16:10	0.005	-0.001	0.005	0.019	0.003	0.006
		16:10 - 16:20	0.012	-0.005	-0.004	-0.001	0.006	0.001
		16:20 - 16:30	0.015	0.000	-0.004	-0.01	0.003	0.001
		16:30 - 16:38	-0.032*	-0.03	-0.002	0.001	-0.005	-0.014
		16:38 - 16:50	0.016	0.052	-0.034	-0.031	-0.025	-0.004
	Days with zero price change		0.02	0.01	0.01	0.00	0.01	0.01

Table 3: Price Discovery per Trade and by Time Period for FTSE 100 Stocks

The Weighted Price Contribution per Trade (WPCT) is computed by the pound volume quintile for FTSE 100 stocks. The WPCT is computed by dividing the WPC per trading interval by the weighted ratio of trades executed during that period (interval). If for each day, $t_{k,s}$ is the number of executed trades in time period *k* for contract *s*, and t_s is the total sum of $t_{k,s}$ for all the periods, then $WPCT_k$ is defined as:

$$WPCT_k = \frac{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right)}{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{t_{k,s}}{t_s}\right)}$$

The final row shows the fraction of days with their close-to-close return equalling 0. Mean WPCs are obtained for each day and the time series standard error of the daily WPCs used for statistical inference. * indicates the WPCTs, which are significantly different from 0 at 0.01 level. The data covers the trading period between 1st October 2012 and 30th September 2013.

		Pound Volume Quintile	Highest	4th	3rd	2nd	Lowest	Overall
Time Periods	Pre-Open/Opening Auction	07:10 - 07:20	99.24*	967.37*	374.12*	-196.72*	-144.38*	219.92*
		07:20 - 07:30	331.57*	-66.32*	-104.47*	805.06*	320.11*	257.19*
		07:30 - 07:40	94.24*	-634.92*	573.85*	-2205.55*	-107.76*	-456.03*
		07:40 - 07:50	1109.12*	770.30*	-532.08*	253.73*	357.23*	391.66*
		07:50 - 08:00	26.74*	318.75*	338.74*	-72.33*	-36.51*	115.08*
	Open-Close/NTH	08:00 - 08:10	1.93	8.56*	12.20*	11.37*	14.17*	9.64*
		08:10 - 08:20	2.36	3.30	2.09	3.23	3.59	2.91
		08:20 - 08:30	1.64	1.09	1.80	2.10	2.06	1.74
		08:30 - 08:40	2.66	0.94	1.58	2.38	1.57	1.83
		08:40 - 08: 50	1.73	1.49	1.64	2.40	2.06	1.86
		08:50 - 09:00	1.40	0.28	1.56	1.75	0.31	1.06
		09:00 - 16:00	0.50	0.62	0.54	0.58	0.63	0.58
		16:00 - 16:10	0.17	-0.03	0.19	0.60	0.10	0.21
		16:10 - 16:20	0.37	-0.15	-0.13	-0.02	0.14	0.04
		16:20 - 16:30	0.31	0.00	-0.09	-0.17	0.05	0.02
	Closing Auction/Post Close	16:30 - 16:38	-0.58	-2.95	-0.17	0.07	-0.16	-0.76
		16:38 - 16:50	28.05*	84.35*	-54.55*	-38.36*	-21.72*	-0.45

Days with '0' price change	0.02	0.012	0.008	0.00	0.012	0.0104

Table 4: Adverse Selection Costs by Period for FTSE 100 Stocks

The table shows adverse selection costs components for FTSE 100 stocks trading between 1st October 2012 and 30th September 2013. The estimates are computed by estimating the following time series model for each stock and time period using ordinary least squares:

$$\Delta P_{k,t} = \beta_{1,k} Q_{k,t} + \beta_{2,k} Q_{k,t-1} + \beta_{3,k} Q_{A,t-1} + e_t$$

where $\Delta P_{k,t}$ is the change in price from the previous retained trade, $Q_{k,t}$ is equal to 1 (-1) when the transaction at period t for stock k was a market maker sell (buy) and $Q_{A,t-1}$ is the aggregate buy-sell indicator used in encapsulating portfolio trading pressure, it equals 1(-1, 0) when the sum of $Q_{k,t-1}$ across all FTSE stocks in the sample is positive (negative, zero). The adverse selection cost component is given as: $2(\beta_{2,k} + \beta_{1,k})$. The lower level quintile observations are very low in number, and thus could not provide robust estimates, hence their exclusion from the estimated contents in the table below. The standard deviations of the adverse selection costs estimates are given in parenthesis. Wilcoxon-Mann-Whitney (tie-adjusted) tests are used to determine whether pre-open or post-NTH values are significantly different from the NTH period. The pre-open or post-NTH periods that differ from the NTH at 1% level are denoted with *.

Pound Volume Quintile	**Pre-Open**		**Normal Trading Hours (NTH)**	**Post-NTH**	
	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)	(08:00:30-16:30)	Closing Auction (16:30:01-16:38)	Post-Close (16:38:01-16:50)
Highest	0.102*	0.935*	0.004	0.041*	0.093*
	(0.090)	(0.456)	(0.003)	(0.033)	(0.060)
4	0.069*		0.002	0.027*	0.072*
	(0.049)	-	(0.001)	(0.014)	(0.031)
3	0.016*	-	0.001	0.021*	0.039*
	(0.010)		(0.0006)	(0.013)	(0.018)
2	0.014*	-	0.001	0.006*	0.016*
	(0.011)		(0.0007)	(0.003)	(0.010)
Lowest	0.046*	-	0.005	0.023*	0.061*
	(0.013)		(0.002)	(0.008)	(0.029)
Overall	0.049*	0.935*	0.003	0.024*	0.056*
	(0.033)	(0.456)	(0.002)	(0.011)	(0.027)

Appendix

List of stocks used in this study

ISIN	RIC	Constituent name	Index Weight (%)	Country	ICB Supersector Code
GB00B02J6398	ADM.L	Admiral Group	0.14	UK	8500
GB0000282623	AMEC.L	Amec	0.19	UK	0500
GB00B1XZS820	AAL.L	Anglo American	1.19	UK	1700
GB0000456144	ANTO.L	Antofagasta	0.17	UK	1700
GB0000595859	ARM.L	ARM Holdings	0.83	UK	9500
GB0006731235	ABF.L	Associated British Foods	0.39	UK	3500
GB0009895292	AZN.L	AstraZeneca	2.41	UK	4500
GB0002162385	AV.L	Aviva	0.70	UK	8500
GB0009697037	BAB.L	Babcock International Group	0.26	UK	2700
GB0002634946	BAES.L	BAE Systems	0.88	UK	2700
GB0031348658	BARC.L	Barclays	2.56	UK	8300
GB0008762899	BG.L	BG Group	2.41	UK	0500
GB0000566504	BLT.L	BHP Billiton	2.31	UK	1700
GB0007980591	BP.L	BP	4.89	UK	0500
GB0002875804	BATS.L	British American Tobacco	3.77	UK	3700
GB0001367019	BLND.L	British Land Co	0.35	UK	8600
GB0001411924	BSY.L	British Sky Broadcasting Group	0.51	UK	5500
GB0030913577	BT.L	BT Group	1.62	UK	6500
GB00B23K0M20	CPI.L	Capita	0.39	UK	2700
GB00B033F229	CNA.L	Centrica	1.14	UK	7500
GB0005331532	CPG.L	Compass Group	0.93	UK	5700
IE0001827041	CRH.I	CRH	0.64	UK	2300
GB0002335270	CRDA.L	Croda International	0.21	UK	1300
GB0002374006	DGE.L	Diageo	2.97	UK	3500
GB00B19NLV48	EXPN.L	Experian	0.71	UK	2700
GB0009252882	GSK.L	GlaxoSmithKline	4.60	UK	4500
JE00B4T3BW64	GLEN.L	Glencore Xstrata	1.94	UK	1700
GB00B1VZ0M25	HRGV.L	Hargreaves Lansdown	0.13	UK	8700
GB0005405286	HSBA.L	HSBC Hldgs	7.48	UK	8300
GB0004579636	IMI.L	IMI	0.28	UK	2700
GB0004544929	IMT.L	Imperial Tobacco Group	1.34	UK	3700

GB00B85KYF37	IHG.L	InterContinental Hotels Group	0.28	UK	5700
GB0033195214	KGF.L	Kingfisher	0.55	UK	5300
GB0031809436	LAND.L	Land Securities Group	0.43	UK	8600
GB0005603997	LGEN.L	Legal & General Group	0.69	UK	8500
GB0008706128	LLOY.L	Lloyds Banking Group	2.13	UK	8300
GB0031274896	MKS.L	Marks & Spencer Group	0.48	UK	5300
GB0005758098	MGGT.L	Meggitt	0.26	UK	2700
GB00B8L59D51	MRON.L	Melrose Industries	0.23	UK	2700
GB0006043169	MRW.L	Morrison (Wm) Supermarkets	0.36	UK	5300
GB00B08SNH34	NG.L	National Grid	1.63	UK	7500
GB0032089863	NXT.L	Next	0.47	UK	5300
GB00B77J0862	OML.L	Old Mutual	0.55	UK	8500
GB0006776081	PSON.L	Pearson	0.61	UK	5500
GB0007099541	PRU.L	Prudential	1.76	UK	8500
GB00B24CGK77	RB.L	Reckitt Benckiser Group	1.75	UK	3700
GB00B2B0DG97	REL.L	Reed Elsevier	0.59	UK	5500
GG00B62W2327	RSL.L	Resolution	0.26	UK	8500
GB0007188757	RIO.L	Rio Tinto	2.26	UK	1700
GB00B63H8491	RR.L	Rolls-Royce Holdings	1.25	UK	2700
GB00B7T77214	RBS.L	Royal Bank Of Scotland Group	0.45	UK	8300
GB00B03MLX29	RDSa.L	Royal Dutch Shell A	4.65	UK	0500
GB00B03MM408	RDSb.L	Royal Dutch Shell B	3.22	UK	0500
GB0006616899	RSA.L	RSA Insurance Group	0.27	UK	8500
GB0004835483	SAB.L	SABMiller	1.78	UK	3500
GB00B8C3BL03	SGE.L	Sage Group	0.22	UK	9500
GB00B019KW72	SBRY.L	Sainsbury (J)	0.33	UK	5300
GB0002405495	SDR.L	Schroders	0.17	UK	8700
GB00B1FH8J72	SVT.L	Severn Trent	0.25	UK	7500
GB0009223206	SN.L	Smith & Nephew	0.41	UK	4500
GB00B1WY2338	SMIN.L	Smiths Group	0.33	UK	2700
GB0007908733	SSE.L	SSE	0.85	UK	7500
GB0004082847	STAN.L	Standard Chartered	1.76	UK	8300
GB00B16KPT44	SL.L	Standard Life	0.49	UK	8500
GB0008847096	TSCO.L	Tesco	1.73	UK	5300

GB0001500809	TLW.L	Tullow Oil	0.56	UK	0500
GB00B10RZP78	ULVR.L	Unilever	1.77	UK	3500
GB00B39J2M42	UU.L	United Utilities Group	0.28	UK	7500
GB00B16GWD56	VOD.L	Vodafone Group	6.31	UK	6500
JE00B8N69M54	WOS.L	Wolseley	0.52	UK	2700
		Total weight	91.23		